The Secular and Cyclic Determinants of Capitalization Rates: *The Role of Property Fundamentals, Macroeconomic Factors, and "Structural Changes"*

SERGUEI CHERVACHIDZE, JAMES COSTELLO, AND WILLIAM WHEATON

SERGUEI CHERVACHIDZE is a capital markets economist at CBRE Econometric Advisors and a doctoral candidate in economics at the University of Houston in Houston, TX.
schervachidze@twr.com

JAMES COSTELLO is a principal at CBRE Econometric Advisors in Boston, MA.
jcostello@twr.com

WILLIAM WHEATON is a principal at CBRE Econometric Advisors and a professor of economics at the Massachusetts Institute of Technology in Cambridge, MA.
wheaton@mit.edu

In this article, we revisit many studies that have attempted to explain the determinants of real estate capitalization rates and we introduce several new innovations.[1] First, we are able to show that certain macroeconomic factors, in addition to risk-free Treasury rates, greatly impact cap rates. The two factors are the general corporate risk premium operating in the economy and the net amount of debt issued in the economy, or liquidity. The addition of these factors greatly adds to the ability of previous models to explain the rise of cap rates in the early 1990s, the secular fall of cap rates in the last decade, and the rise of cap rates during the recent financial crisis. In addition, we use innovative tests for structural shifts in the cap rate and include all of these macroeconomic factors. Our tests identified two distinct periods of structural change that could be thought of as a type of investor sentiment; the first was a period of negative sentiment from 1991 to 1996 and the second was a period of positive sentiment from 2002 to 2007.

Methodologically, our analysis uses a large and robust quarterly panel dataset of 30 U.S. metropolitan areas from 1980 Q1 through 2007 Q4. We compare models using traditional measures of within-sample fit and also examine how the models behave in in-sample backtest forecasts.

The article is organized as follows. In the next section, we review the literature on cap rates. Next, we detail our panel database and outline the basic econometric model that we use. Then, we present our results using models as they exist in the literature and then with the introduction of additional macroeconomic variables. We next turn the discussion toward tests for structural shifts in cap rates and present the results when parameter shifts were allowed during these identified periods. Finally, we compare the ability of the three models to explain changes in cap rates over the last three decades using traditional measures of fit and examine their relative performance using within-sample backtest forecasts. We conclude with a discussion and interpretation of our findings.

BACKGROUND AND RELATED LITERATURE

The starting point of this article is a long literature on the determinants of real estate capitalization rates. A number of studies have modeled cap rates as an adjustment around equilibrium values that are, in turn, determined by real estate fundamentals, such as rent levels and rental growth, as well as risk-free interest rates (see Sivitanides et al. [2001], Hendershott and MacGregor [2005a, 2005b], Chen, Hudson-Wilson, and Nordby [2004], Chichernea et al. [2008], Sivitanidou and Sivitanides [1999], and Shilling and Sing [2007]). Archer and Ling [1997] included a metric for a general risk premium over the risk-free rate. In this article, we draw on the literature to specify what we term a standard, literature-based model that emphasizes real estate fundamentals in determining capitalization rates. We specifically draw on Sivitanides et al. [2001] for this task. A related line of inquiry asks about the efficiency of real estate pricing, in particular whether cap rates have the expected predictive power in explaining subsequent real estate returns (Hendershott and MacGregor [2005a, 2005b] and Ghysels, Plazzi, and Valkanov [2007]).

To this literature we add the idea that macroeconomic capital flows and the availability of debt may also impact capital pricing. Theoretical models of asset pricing in which capital flows play an obvious role can be found in the literature (for example, Geltner et al. [2007] and Wheaton [1999]). Some recent work on real estate returns has begun to empirically include the dynamics of commercial real estate capital flows (Ling and Naranjo [2003, 2006] and Fisher, Ling, and Naranjo [2007]). Concern about the obvious simultaneity between flows and returns has been raised regarding this line of research. Ling and Naranjo [2003, 2006] found that capital flows into public (securitized) markets do not predict subsequent returns, but returns do impact subsequent capital flows. Other studies, however, have found evidence that lagged institutional capital flows do have an effect on current returns at the aggregate level (Fisher, Ling, and Naranjo [2007]). In our study, we avoided the simultaneity issue by using aggregate U.S. capital flows rather than those directed at real estate. Furthermore, we did not consider equity, but only the availability and issuance of overall debt in the economy.

Thus, we drew on a long macroeconomic literature concerning the role of debt availability in generating asset demand and asset "bubbles" (Kiyotaki and Moore [1997] and Miller and Stiglitz [2008]). In recent years, these ideas have spawned a literature on what is termed "global imbalances" (see Caballero, Farhi, and Gourinchas [forthcoming]). This thesis postulates that due to the heterogeneity in countries' abilities to produce financial assets for domestic savers, large capital flows from developing countries to developed ones have tremendously increased debt availability and have bid up asset prices, including those of real estate. In this article, we specifically examine whether trends in the growth of overall debt in the U.S. economy can help in explaining movements in real estate cap rates.

This article goes one step further and introduces a novel test to determine whether the parameters of our cap rate model are changing during certain periods. When we find such periods the question naturally arises as to how to interpret these changes. This exercise in some ways is related to the general finance literature on the concept of investor sentiment. One approach to this topic is by Baker and Wurgler [2007] who defined investor sentiment as a biased belief about the future growth rate of cash flows and investment risks based on the present information set. Hirshleifer [2001], as well as Barberis and Thaler [2003], offered comprehensive reviews of a long literature on biased investor beliefs. Empirical studies of investor sentiment about stock returns often employ principal component analysis in addition to some form of a more direct sentiment proxy. Articles of note include Brown and Cliff [2004, 2005] and Baker and Wurgler [2006, 2007].

As Clayton, Ling, and Naranjo [2009] explained, this sentiment-driven mispricing also requires some form of limits to arbitrage, wherein nontrivial transaction costs and short-selling constraints must prevent arbitrageurs from taking fully offsetting positions to correct the mispricing. Baker and Stein [2004] provided a specific example of pricing under short-selling limitations. Pessimistic investors who would otherwise take short positions may sit on the sidelines because they believe that assets are overvalued relative to fundamentals. As a result, market-clearing prices are determined on the margin by overly optimistic investors. Transaction costs are especially high in the real estate sector, and there are significant constraints on short-selling. The interplay between sentiment (with the attendant limitations on efficient fundamentals-based pricing) and fundamental factors could easily explain why model parameters change and forecasts diverge from fundamental values over certain periods.

This article is most closely related to the recent work by Clayton, Ling, and Naranjo [2009]. We extend their article in four areas. First, rather than use a two-step error-correction specification to model cap rates, we relied on the suggestion of Gallin [2006] and used a single-step adjustment model. Second, instead of relying on a short national time series, we gained immense degrees of freedom by working with a panel database that combines the time series of 30 U.S. markets. Third, Clayton, Ling, and Naranjo [2009] tried to directly measure investor sentiment with a survey metric, but we let the data tell us when pricing parameters are changing in ways not explained by any of the data. Finally, we specifically examined the role of economy-wide debt availability. Over the last decade in particular, the widespread availability of debt followed by the sudden contraction of this source of capital is generally believed to be an important factor in explaining the drop in cap rates from 2000 to 2006 as well as their sudden recent rise.

DATA AND METHODOLOGY

Like most other studies of U.S. capitalization rates, we utilized the appraisal-based values reported since the early 1980s by the National Council of Real Estate Fiduciaries (NCREIF). NCREIF cap rates have often been criticized for not being based on actual sales transactions, but in the U.S. they are the sole source of data that goes back several decades. Our data on rental rates comes from Torto Wheaton Research and utilizes their rent indices, which are created by applying hedonic analysis to data on thousands of actual lease transactions in each market.

We incorporated two macroeconomic factors in our research. The first factor is Moody's risk premium for corporate AAA bonds over the 10-year Treasury bond rate. The second factor is the growth in total (public and private) net debt outstanding (Federal Reserve) divided by GDP. This variable is slightly different from the growth of debt relative to that of GDP. In our measure, GDP acts as a deflator, rather than as a comparable benchmark. In Exhibits 1 and 2, we illustrate these data for the NYC office market. In Exhibit 1, we compare the NCREIF cap rate with the 10-year Treasury rate and the deflated rent index for office properties in that city. In Exhibit 2, we compare the cap rate with the bond risk premium and with our measure of the growth in GDP-deflated debt.

As in many U.S. markets, office cap rates moved between 6% and 10% over the last two decades, but then declined sharply to almost 4% in the last four years. During this time, constant-dollar rents varied from index values of 0.7 to 1.3. The risk premium rose steadily from 50 basis points (bps) in 1980 to more than 200 bps in 2000, and then fell rapidly to less than 100 bps, until it rose again in the current credit crisis. Perhaps most interestingly, our index of the annual nominal growth in debt divided by GDP shows yearly increases ranging from 10% to more than 30%. Two periods of great expansion in debt were the mid-1980s and the last four years.

Using these data, we estimated a separate model for each type of real estate (e.g., office, retail, and so forth). The macroeconomic data is the same for each type of real estate—only the rent series and cap rates vary across property categories. For each model, we used an unbalanced panel (i.e., the panel misses values for some observations) that spans the period from 1980 Q1 to 2007 Q4. Each panel has approximately 30 MSA markets (a statistical summary of the dataset is provided in the appendix). As a result, in spite of missing values, the dataset contains more than 2,400 usable observations for each property type and generates high degrees of freedom. A note on our estimation approach is warranted at this stage. All models in this article are estimated using the fixed effects panel method

EXHIBIT 1

NYC Office Cap Rate, Real T-Bond, Rent Index

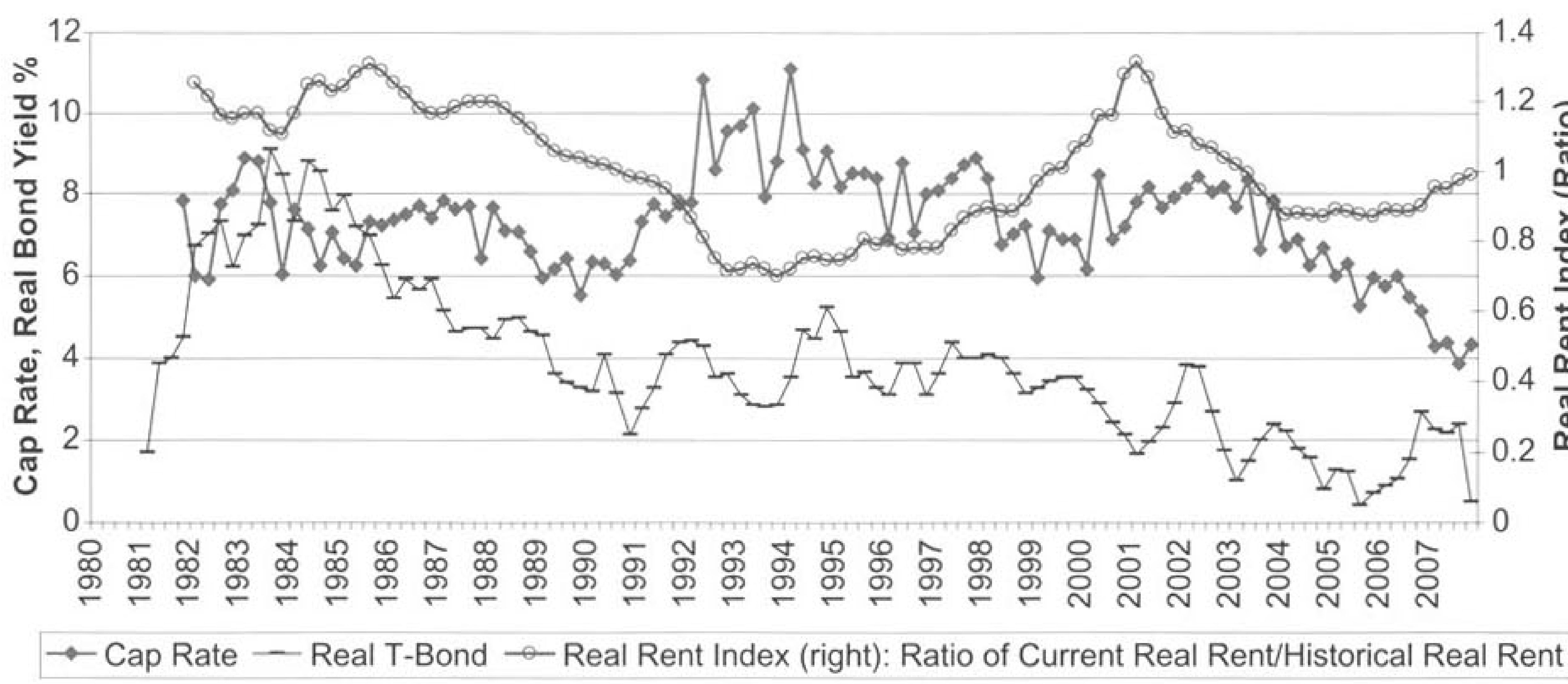
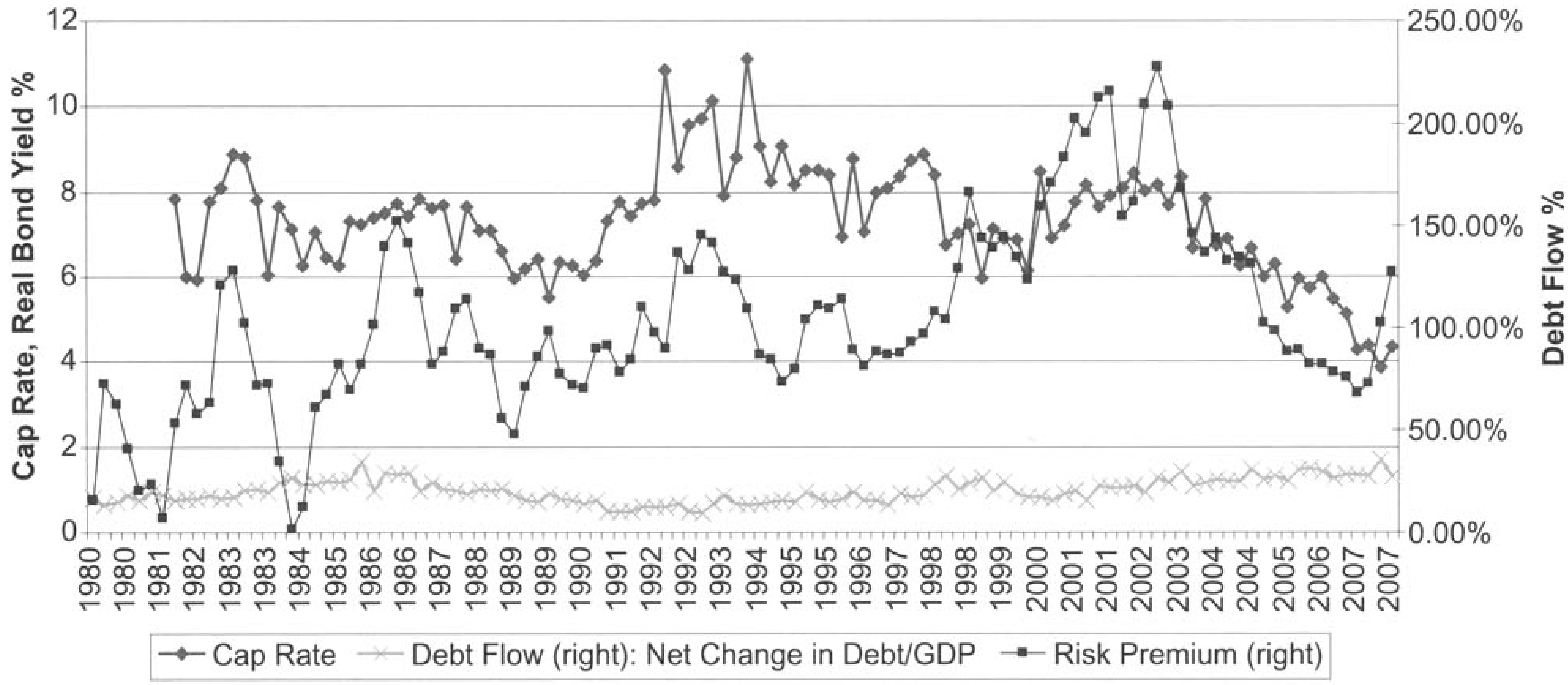


Exhibit 2
NYC Office Cap Rate, Macro Risk Premium, Debt Flow



(see Greene [2004]) with White's heteroskedasticity correction for standard errors (White [1980]).

The rationale behind this estimation strategy is compelling. The fixed effects panel technique allows us to use both time-series and cross-sectional (between MSA) variation, which increases the efficiency of the OLS estimators (see Greene [2004]) and generates better estimates of model coefficients. Furthermore, our estimation strategy explicitly models for the time-invariant differences (hence, the name "fixed effects") in trends between the cross-sectional MSA units. This framework is consistent with theoretical expectations that market-specific unobserved characteristics will lead to permanent differences in capitalization rate trends across markets, and the fixed effects method allows us to estimate the effect of these unobservables and to test for their statistical significance. Finally, the higher estimator efficiency increases the power of post-estimation tests, which allows for better inferences about results. Exhibit 3 lists all variables used in this article as well as their sources. The statistical summary for these variables is given in the appendix.

Exhibit 3 shows that the real rent index is the only right-side variable that exhibits cross-sectional variation, with the other national macroeconomic variables being the same for each cross-sectional unit. As such, this setup prevents us from including time trends or time effects in the models because these would cancel the effect of national macroeconomic variables.

THE STANDARD SPECIFICATION: MARKET FUNDAMENTALS AND TREASURY RATES

The intent of the first, most basic model is to reflect the standard approach used in the literature to date (see Sivitanides et al. [2001]). This literature does not apply a two-step error-correction process (see Gallen [2006]), but instead postulates that cap rates simply follow an adjustment process around equilibrium values. The equilibrium is estimated at the same time as the adjustment and is determined by two sets of influences: 1) influences of the discount rate that reflect both the opportunity cost of capital and systematic market risk, and 2) fundamental factors that shape investors' income growth expectations. This is in keeping with the literature, which usually uses rental fundamentals and some proxy for the interest rate to explain cap rates.

As discussed earlier, the standard specification we used is given in Equation (1). It is formulated so as to be comparable to more extended specifications used later in the article,

$$\begin{aligned}\mathrm{Log}(C_{j,t}) = a_0 + a_1\log(C_{j,t-1}) + a_2\log(C_{j,t-4}) \\ + a_3\log(RRI_{j,t}) + a_4RTB_t + a_7Q2_t \\ + a_8Q3_t + a_9Q4_t + a_{10}D_j \qquad (1)\end{aligned}$$

The preceding is a panel specification where j is Metropolitan Statistical Area (MSA) and t is time. This is

EXHIBIT 3
Main Variables Used in Specifications

Variable	Description	Source
$C_{j,t}$	**Capitalization rate** from NCREIF database calculated from net operating income and NCREIF portfolio values.	National Council of Real Estate Investment Fiduciaries (NCREIF)
$RRI_{j,t}$	**Real rent index** calculated as a ratio of real rent index from Torto Wheaton rent database for a given MSA in a given quarter to the historical average of real rent for this MSA: $RRI_{j,t-s}$ = $Real\ Rent_{j,t}/Mean(Real\ Rent_j)$,where the mean is calculated over the sample time period for each *j*.	CBRE Torto Wheaton Research Rental Index. The index is hedonically derived and controls for quality.
RTB_t	**Real T-bond yield** calculated as nominal yield minus inflation rate.	Federal Reserve
$SPREAD_t$	**Risk premium** calculated as the spread between Moody's AAA Corporate Bond Index and the 10-year T-bond yield.	Federal Reserve
$DEBTFLOW_t$	**Debt flow** calculated as a ratio of *Total Net Borrowing* and *Lending*, from the Federal Reserve's Flow of Funds Database, to that quarter's nominal GDP level (both variables are annualized quarterly values): $DEBTFLOW_t = Total\ Net\ Borrowing\ and\ Lending_t/GDP_t$	Federal Reserve

estimated separately for each property sector. The variables are as follows:

$C_{j,t}$: Capitalization rate from NCREIF database calculated from net operating income and asset values.
$RRI_{j,t}$: Real rent index calculated as a ratio of real rent data from the Torto Wheaton rent database for a given MSA in a given quarter to the historical average of real rent for this MSA,

$$RRI_{j,t-s} = \text{Real Rent}_{j,t}/\text{Mean}(\text{Real Rent}_j) \qquad (1.1)$$

where the mean is calculated over the sample time period for each j.
RTB_t: Real T-bond yield, calculated as the nominal yield minus the inflation rate, that proxies the risk-free rate and the opportunity cost of capital.
$Q2_t$, $Q3_t$, $Q4_t$: Seasonal dummies to remove seasonality.
D_j: Fixed market-level effects associated with each MSA.

In terms of theoretical priors on the signs of coefficients, the risk-free rate, *RTB*, is expected to have a positive effect on the cap rates. The effect of the real rent index, *RRI*, however, is theoretically ambiguous (Sitivanides et al. [2001]) and depends on whether investors are forward looking or backward looking. In the case of forward-looking expectations, high rent levels (as compared to historical means) will inform investors that the market is at the peak of the cycle and that a downward adjustment is in order, thus causing investors to expect lower cash flows in the future. If investors possess this paradigm, *RRI* will have a positive effect on capitalization rates. Alternatively, if investors are backward looking (as evidenced by Sivitanides et al.), they will project current rent growth into the future and will accordingly bid up asset values. This mindset implies a negative effect of the rent index on cap rates. These expectations are in line with existing literature. Finally, the MSA-level fixed effects (dummy variables) D_j account for non-varying market-specific characteristics not explicitly included in the model.

Exhibit 4 depicts estimation results for this basic model on our dataset. The real T-bond coefficient has the expected positive sign across property sectors and is statistically significant. The real rent index, the variable without an a priori sign expectation, has a statistically significant negative sign, which testifies to the backward-looking behavior of real estate investors and is generally consistent with results in Sivitanides et al. [2001]. The group test for the collective effect of MSA dummies yields insignificant statistics for all property types but retail, and individual tests show that some MSAs are significant, while others are not. This finding is in line with those of

EXHIBIT 4

Multiple Regression Results (Standard Literature-based Specification with Rents, T-Bonds, and Inflation, Includes Fixed Effects)

Independent Variable	Office	Industrial	Multifamily	Retail
Constant	0.339 (8.226)	0.402 (10.00)	0.186 (5.401)	0.434 (6.238)
Log(CAP)_{t-1}	0.612 (22.824)	0.563 (24.179)	0.688 (22.971)	0.520 (11.084)
Log(CAP)_{t-4}	0.207 (7.472)	0.231 (9.836)	0.185 (5.832)	0.252 (7.151)
$\text{Log(Real Rent Index)}_t$	–0.038 (–1.810)	–0.047 (–2.315)	–0.158 (–3.708)	–0.134 (–3.800)
Real T-Bond 10-year	0.009 (3.851)	0.008 (4.142)	0.023 (7.646)	0.010 (3.416)
Q2	–0.003 (–0.327)	–0.006 (–0.905)	–0.014 (–2.218)	0.001 (0.103)
Q3	–0.035 (–4.307)	–0.014 (–2.072)	–0.015 (–2.366)	–0.012 (–1.235)
Q4	–0.034 (–4.024)	–0.020 (–2.739)	–0.005 (–0.702)	0.026 (2.758)
R-square (adjusted)	0.585	0.525	0.824	0.542
Number of cross-sectional units (MSA markets)	38	38	34	27
Number of usable observations (excludes missing values)	2656	2976	1781	1903
Test of group significance of fixed effects	F(37,*) = 0.69479 Significance Level: 0.91877966	F(37,*) = 0.55697 Significance Level: 0.98655056	F(33,*) = 0.53677 Significance Level: 0.98625294	F(26,*) = 1.78109 Significance Level: 0.00842397

Notes: The dependent variable is Log(Cap). t-statistics are in parentheses. Estimate of fixed effects omitted for brevity. All data are quarterly from 1980 Q1 through 2007 Q4.

Sitivanides et al., indicating that some markets exhibit statistically significant differences in average cap-rate levels.

EXTENDED MODEL SPECIFICATIONS: ADDING RISK PREMIUM AND DEBT FLOWS

In this specification, we attempt to improve on the existing literature by including two new variables. The first variable is the degree of general risk aversion in the economy (and hence the associated premium demanded by investors for this risk). We measure this with a standardized corporate bond spread. The second variable measures the availability of debt in the economy scaled by GDP. In equilibrium asset-pricing theory, the amount of debt applied to an asset should not impact its price because risk increases commensurately; as just discussed, however, recent economic thinking calls this assumption into question. Macroeconomic theory now regards debt availability as a frequent cause of financial crises, and microeconomic theory argues that debt provides purchase liquidity. Thus, when debt is scarce, real estate transactions become more difficult and prices may fall below the asset's fundamental value. Easy debt, in contrast, encourages real estate transactions and can also inflate prices above an asset's fundamental value—possibly into a "bubble." These two new factors theoretically could play an important role in the determination of cap rates.

Specifically, we extend Equation (1) with the following specification:

$$\begin{aligned}\text{Log}(C_{j,t}) = a_0 + a_1\log(C_{j,t-1}) + a_2\log(C_{j,t-4}) \\ + a_3\log(RRI_{j,t-s}) + a_4 RTB_t \\ + a_5 SPREAD_t + a_6 DEBTFLOW_t \\ + a_7 Q2_t + a_8 Q3_t + a_9 Q4_t + a_{10} D_j \qquad (2)\end{aligned}$$

The model setup is the same as in Equation (1) with the addition of two variables, *SPREAD* and *DEBTFLOW*, as well as the addition of lags to the real rent index for some property types. Details are as follows:

> $RRI_{j,t-s}$: Defined as in Equation (1), except for now there is lag s for some property types; s is different for various property types.
>
> $SPREAD_t$: Economy-wide risk premium over the risk-free rate, calculated as the difference between Moody's AAA Corporate Bond Index and the 10-year T-bond.
>
> $DEBTFLOW_t$: Ratio of the *Change in Total Debt Outstanding* (*Net Borrowing/Lending*) from the Federal Reserve's Flow of Funds Database to that quarter's nominal GDP level (both variables are annualized quarterly values),

$$DEBTFLOW_t = \text{Total Net Borrowing and Lending}_t / GDP_t \qquad (2.1)$$

The expected coefficient signs for the variables carried over from Equation (1) are the same as before. In terms of the new variables, *SPREAD* is expected to have a positive sign (with investors demanding compensation for higher risk in the form of lower asset values for the same stream of net operating income), and *DEBTFLOW* is expected to have a positive effect on asset values (and a negative effect on cap rates) as, ceteris paribus, investors bid up asset values when it becomes easier to trade them. The test of this effect and its magnitude is especially relevant in the current environment in which the general lack of debt financing is postulated to have an important negative influence on real estate asset prices.

The extended model is again estimated using fixed effects with White's heteroskedasticity correction on the same unbalanced panel sample as the one used for the standard model in Equation (1). Results of estimating the extended model in Equation (2) are given in Exhibit 5. It is interesting that all coefficients have the expected signs and are significant across the four property types. It is furthermore of note that the addition of *DEBTFLOW* and *SPREAD* has not changed the sign or significance of the original rental index and Treasury yield variables, suggesting that these new factors are orthogonal to the original factors.

Also, in this setup the real rent index has different lags across the four property types, with the lag length determined by specification search on lag length with the goal of generating the highest significance level for this variable. This difference in lags across property types can be attributed to the fact that investors in different property sectors react with somewhat different dynamics in response to changes in real estate fundamentals. And unlike the case of the model in Equation (1), group tests on the collective significance of MSA fixed effects indicate group significance for all property types except multifamily.[2]

A comparison of estimation results of Equations (1) and (2) show a marked improvement in the performance of the extended specification in Equation (2) vis-à-vis the standard version in Equation (1), across all property types. The extended model results in higher adjusted R-squared statistics, which testifies to the improved fit of the extended model (details on the goodness-of-fit follow later in the article). More importantly, however, the orthogonality and statistical significance of the additional debt and risk-spread variables indicates that these two financial factors are important in the determination of capitalization rates and should be included in capitalization rate models. This finding is in line with theoretical expectations that debt availability, as well as the risk premium demanded by investors, both have strong effects on real estate asset pricing, and that omitting these factors in cap rate models has been a major deficiency in the literature thus far. As such, Equation (2) offers an improvement over the existing literature on modeling capitalization rates.

TESTING FOR STRUCTURAL CHANGES

The addition of a risk premium and a debt flow measure adds greatly to the model and captures some aspects of investors' tolerance for risk and preference for liquidity. Of more general interest, however, is the question of whether investors express a positive or negative

EXHIBIT 5
Multiple Regression Results (Extended Specification with Fixed Effects, No Structural Change)

Independent Variable	Office	Industrial	Multifamily	Retail
Constant	0.535 (11.304)	0.652 (13.419)	0.418 (8.877)	0.635 (9.156)
Log(CAP)_{t-1}	0.526 (18.082)	0.492 (20.040)	0.627 (20.802)	0.428 (8.964)
Log(CAP)_{t-4}	0.193 (6.904)	0.198 (8.591)	0.169 (5.380)	0.225 (6.604)
$\text{Log(Real Rent Index)}_{t-s}$	–0.101 (–3.877)	–0.100 (–4.634)	–0.168 (–3.921)	–0.175 (–5.100)
Lag Length for RRI_s =	*2*	*4*	*0*	*4*
Real T-Bond 10-year	0.013 (4.377)	0.010 (4.687)	0.019 (5.694)	0.016 (4.145)
Risk Spread	0.078 (7.884)	0.053 (7.476)	0.019 (2.978)	0.096 (7.995)
Debt Flow	–0.528 (–8.551)	–0.505 (–9.911)	–0.468 (–7.964)	–0.383 (–5.998)
Q2	0.006 (0.755)	0.001 (0.187)	–0.010 (–1.717)	0.006 (0.721)
Q3	–0.034 (–4.271)	–0.013 (–2.013)	–0.019 (–2.871)	–0.016 (–1.765)
Q4	–0.035 (–4.235)	–0.019 (–2.651)	–0.006 (–0.871)	0.019 (2.127)
R-square (adjusted)	0.612	0.554	0.831	0.580
Number of cross-sectional units (MSA markets)	38	38	34	27
Number of usable observations (excludes missing values)	2656	2948	1781	1903
Test of group significance of fixed effects	F(37,*) = 1.63497 Significance Level: 0.00872398	F(37,*) = 1.35677 Significance Level: 0.07240589	F(33,*) = 1.02724 Significance Level: 0.42401262	F(26,*) = 1.85984 Significance Level: 0.00491232

Notes: The dependent variable is Log(Cap). t-statistics are in parentheses. Estimate of fixed effects omitted for brevity. All data are quarterly from 1980 Q1 through 2007 Q4.

sentiment toward real estate as an asset class. Real estate is different from financial assets, in part because of its physicality and in part because of the leasing structures that underlie its income stream. The relationship between the market rent and income of individual properties is complicated greatly by the various leasing arrangements between tenant and landlord. Thus, we might expect that over time investor preferences for these features of real estate change, and investor expectations about how real estate as an asset class will perform also change.

Our approach to examining investor sentiment is to look for periods of systematic structural change in the parameters of our cap rate models. We examine both patterns of forecast residuals as well as structural changes in the individual model parameters. We test for the existence and direction of these long-term effects by utilizing a panel version of the CUSUM test for structural change that is uniquely suited to this task, as will be further discussed later in the article. This approach takes the best specification thus far, Equation (2), as a baseline model and assumes gradually changing exogenous factors that are responsible for long-run gradual structural change in the model. CUSUM tests, based on recursive estimation, are then used to test for the existence and timing of this long-run structural change.

The CUSUM tests, which operate only in the time dimension, can use up degrees of freedom. Because the MSA fixed effects are often insignificant individually, we chose to eliminate them for the CUSUM testing. The simplified version of the model (omitted MSA-specific fixed effects) then effectively becomes a pooled ordinary least squares (OLS) specification (see Greene [2004] for pooled OLS estimator), but is otherwise identical to the model described in Equation (2). Results for estimating this simplified benchmark model are given in Exhibit 6. All coefficients of the simplified benchmark model are significant and of the same sign as before and have magnitudes similar to the results for the model in Equation (2). As such, Equation (3) is a good benchmark model to be used with CUSUM tests. It is important to note that results for the model in Equation (3) and shown in Exhibit 6 is equivalent to the last stage in recursive regressions used in the tests that follow (because the last stage is estimated on the full sample of data):

$$\begin{aligned}\text{Log}(C_{j,t}) = {} & a_0 + a_1\log(C_{j,t-1}) + a_2\log(C_{j,t-4}) \\ & + a_3\log(RRI_{j,t-s}) + a_4 RTB_t \\ & + a_5 SPREAD_t + a_6 DEBTFLOW_t \\ & + a_7 Q2_t + a_8 Q3_t + a_9 Q4_t \end{aligned} \tag{3}$$

Having specified the baseline model in Equation (3), this model in turn is used in a series of recursive regression-based structural change tests. This cumulative sums test was originally developed by Brown, Durbin, and

EXHIBIT 6

Multiple Regression Results (Pooled OLS Specification: Benchmark Version Used in CUSUM Tests)

Independent Variable	Office	Industrial	Multifamily	Retail
Constant	0.471 (13.357)	0.578 (16.023)	0.343 (10.134)	0.502 (12.986)
Log(CAP)_{t-1}	0.550 (33.056)	0.512 (32.300)	0.651 (34.136)	0.459 (22.481)
Log(CAP)_{t-4}	0.214 (13.148)	0.215 (13.667)	0.184 (9.931)	0.250 (12.644)
$\text{Log(Real Rent Index)}_{t-s}$	−0.068 (−3.004)	−0.077 (−4.032)	−0.199 (−5.180)	−0.126 (−4.278)
Lag Length for RRI_s =	*2*	*4*	*0*	*4*
Real T-Bond 10-year	0.010 (3.940)	0.008 (4.742)	0.017 (5.545)	0.014 (5.741)
Risk Spread	0.068 (8.173)	0.047 (7.006)	0.015 (2.286)	0.086 (9.482)
Debt Flow	−0.490 (−9.000)	−0.462 (−10.213)	−0.415 (−7.647)	−0.382 (−6.479)
Q2	0.005 (0.671)	0.001 (0.094)	−0.010 (−1.595)	0.007 (0.755)
Q3	−0.034 (−4.208)	−0.014 (−1.937)	−0.017 (−2.696)	−0.014 (−1.566)
Q4	−0.034 (−4.236)	−0.019 (−2.718)	−0.005 (−0.795)	0.021 (2.274)
R-square (adjusted)	0.611	0.553	0.831	0.575
Number of cross-sectional units (MSA markets)	38	38	34	27
Number of usable observations (excludes missing values)	2656	2948	1781	1903

Notes: The dependent variable is Log(Cap). t-statistics are in parentheses. This is a pooled OLS specification: time series and cross-sectional observations pooled together and estimated via OLS with heteroskedasticity corrected errors All data are quarterly from 1980 Q1 through 2007 Q4.

Evans [1975]. The panel version of the test follows the Maskus [1983] approach. The objective of this test is to detect statistically significant changes in the model structure by using a test statistic, which is based on recursively estimated regression residuals from the model. After performing CUSUM tests, we extended the analysis by plotting out the path of recursive model coefficients (as well as their standard error bands). This approach allows us to examine if certain variables are responsible for structural change or whether structural change should be attributed to a general factor (Dinardo and Johnston [1996]).

Intuitively, the essence of the CUSUM test is a plot of residuals from fitting a baseline model (in this case the model in Equation (3)) recursively, that is, adding a vector of observations corresponding to each additional period and then re-estimating the whole model with the expanded dataset. This generated CUSUM series is plotted against a pair of lines symmetrically above and below the zero line such that the probability is that the CUSUM plot will cross either line at the desired level of significance. If the plotted CUSUM series simply moves around the zero mean line, there is no evidence of the model structure changing over time. And if the CUSUM series crosses either of the test lines, such crossing would indicate statistically significant evidence (at a chosen level of significance) of structural change affecting the model.

Exhibit 7 plots the CUSUM, along with the associated 10% significance bands for each property type. This set of recursive CUSUMs is based on iterations starting in 1987 Q1 (1988 Q1 for multifamily). For all property types, the model underforecasts in the early 1990s with statistically significant structural change occurring around 1991, which is evident from the CUSUM plots crossing the upper significance band during that period. Significantly positive CUSUM values indicate that the additional data from this period has cap rates that are constituently higher than the ones predicted by the model; this could be interpreted as negative investor sentiment. Subsequently, across all property types, CUSUMs began to decline by the late 1990s and early 2000s, then the process reverses, and the process again passes the 10% significance band (except for office). This move could indicate underforecasting or positive investor sentiment.[3]

Also interesting is that the structural change indicated by these plots is gradual, with the CUSUM values taking a long time to reach significance bands once they begin deviating from the zero-line mean. Thus, models with a shorter sample will not capture this gradual shift. Other tests for structural change (e.g., the rolling dummy tests by Quandt [1960]) that are designed to detect radical shifts in relationships that are preceded and followed by long periods of stability will not capture this dynamic either.

Before drawing conclusions as to the nature of this structural change, we examined recursively estimated coefficients of the model with their two standard error bands. Exhibit 8 illustrates this investigation, but only for office properties. This technique is useful for detecting whether any structural change can be attributed to a particular variable. These graphs can be interpreted as follows. If a coefficient (along with the error bands) moves radically from its previous trend, then the structural change (Dinardo and Johnston [1996]) is attributed to a changing coefficient for that variable. The coefficients generally start out as not significantly different from zero and then meander toward their expected statistically significant values as the recursive model picks up observations. They do not exhibit any radical shifts. This conclusion holds for the other property types as well. In effect we cannot attribute the observed structural change to slowly varying preferences for risk, liquidity, or rental income growth. These significance profiles indicate that the gradually occurring structural change is, in fact, exogenous to the model. The fact that such slowly occurring hard-to-detect structural change is present in the determination of capitalization rates is one of the main findings of this article.

COMPARATIVE ANALYSIS OF ALTERNATIVE SPECIFICATIONS

In light of these findings on the existence of gradual changes in model structure, a natural next step is to extend the model in Equation (2) further by explicitly accounting for structural change and to test whether this model performs better in explaining capitalization rates than the previous approaches in Equations (1) and (2). We accomplish this by adding a structural-change dummy variable to the specification in Equation (2)—a time dummy that implies a change in the constant (see Chow [1960]). This dummy is designed to capture the period of structural change identified in the CUSUM analysis from 2000 to 2004. Although an imperfect device for modeling gradually occurring structural shifts, it is nonetheless useful for examining whether

EXHIBIT 7

CUSUM Plots: 10% Significance Bands. Iteration Starting in 1987 Q1 (1988 Q1 for Multifamily)

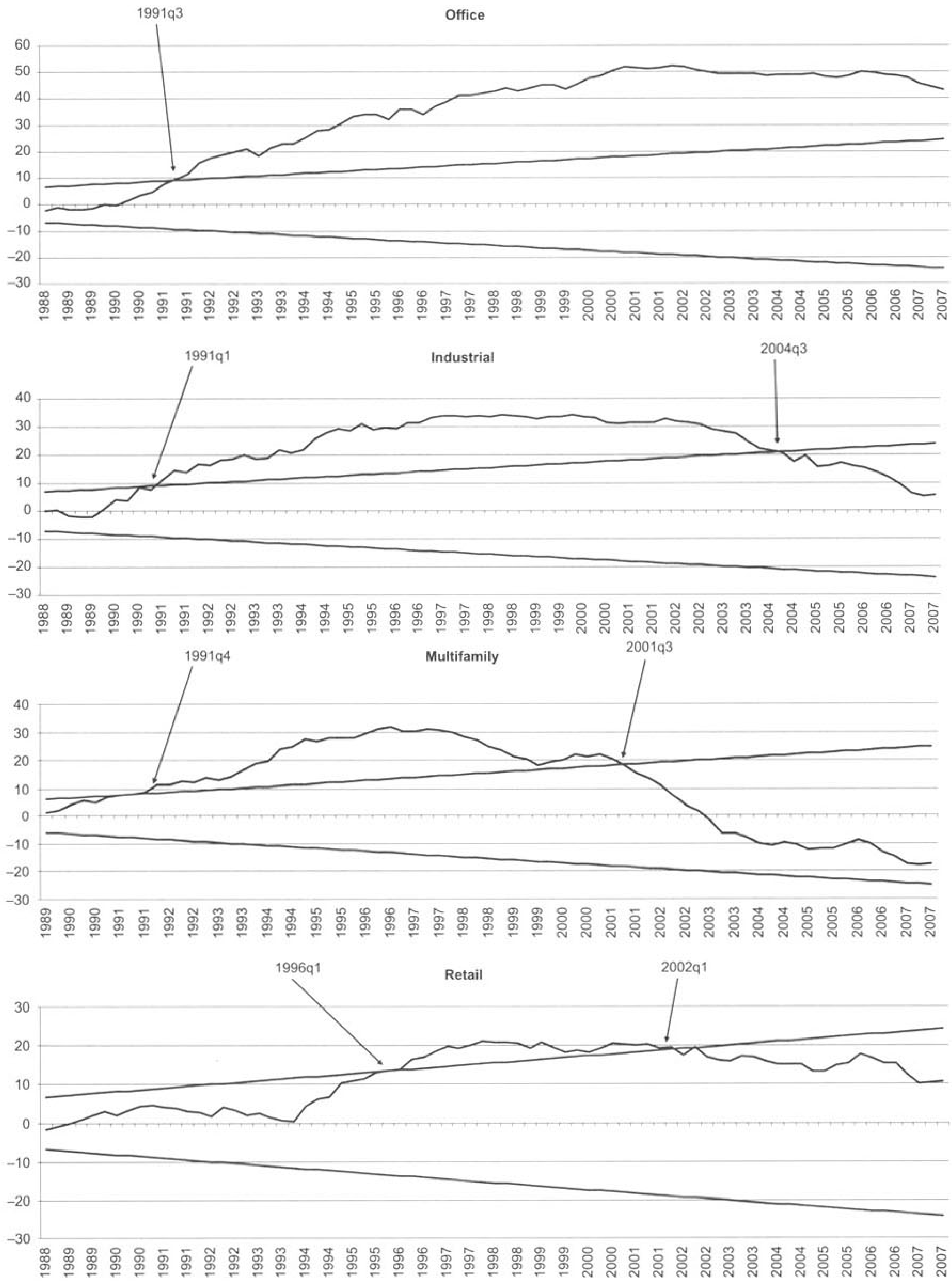
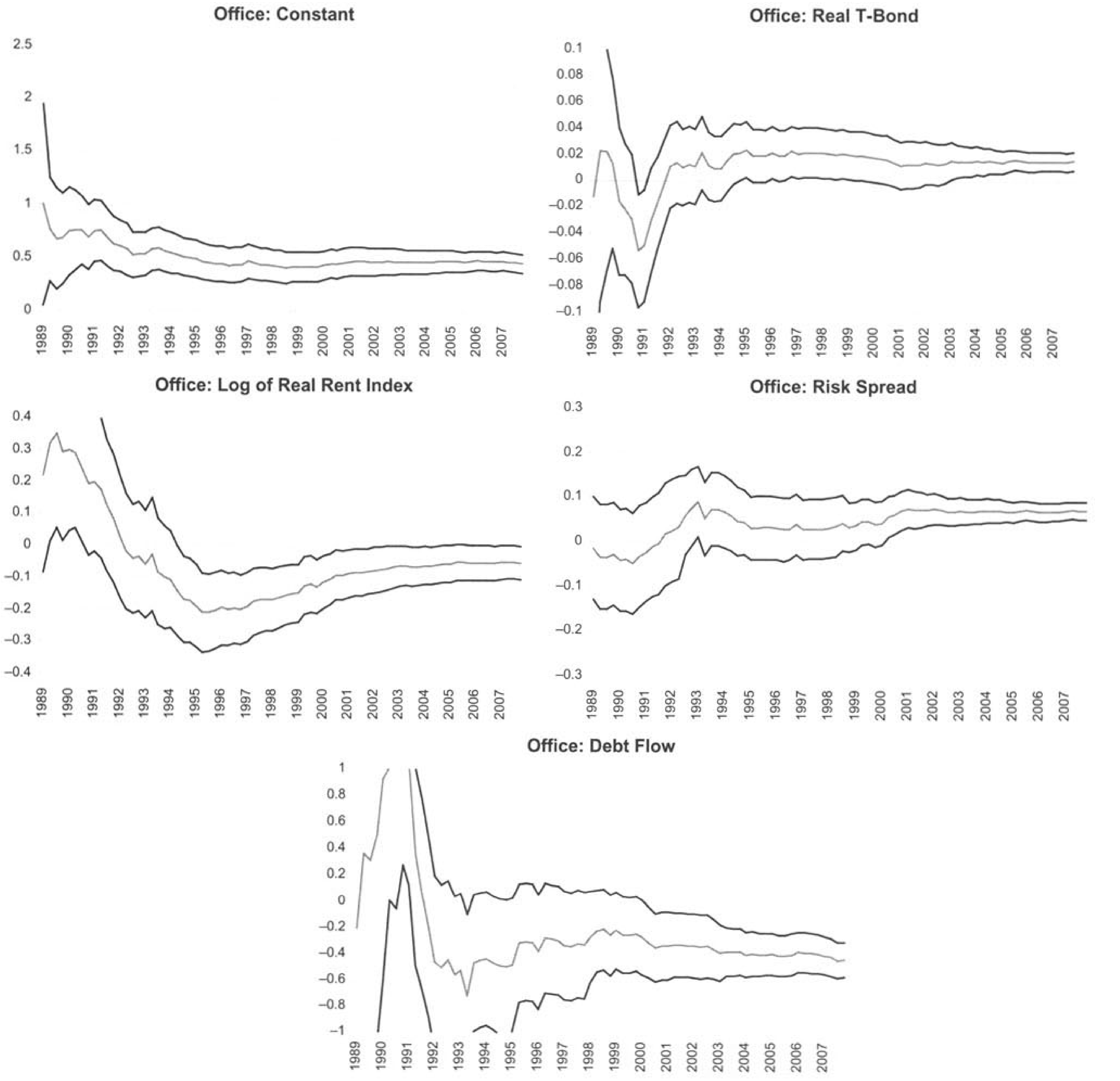


Exhibit 8

Example of Recursive Coefficient Tests for Structural Change: Recursive Coefficients Change and +/– Two Standard Error Bands



accounting for these shifts improves model performance. The resulting specification is

$$\begin{aligned}\text{Log}(C_{j,t}) = {} & a_0 + a_1 yearq + a_2\log(C_{j,t-1}) \\ & + a_3\log(C_{j,t-4}) + a_4\log(RRI_{j,t-s}) \\ & + a_5 RTB_t + a_6 SPREAD_t \\ & + a_7 DEBTFLOW_t + a_7 Q2_t + a_8 Q3_t \\ & + a_9 Q4_t + a_{10} D_j \end{aligned} \tag{4}$$

The term *yearq* is the relevant structural shift dummy variable. The timing of the structural shift was determined by maximizing the *t*-statistic on the dummy during the 2000–2004 period subject to the constraint that the independent variables retain their correct signs and significance; this produced different dates for the structural breaks across property types. The exact timing of the structural change is not significant, however, because CUSUM tests show this change is gradual and any single date would be arbitrary. The important application is simply to extend the model with a factor for structural change in the relevant time period (i.e., 2000–2004), and then to compare this specification with the earlier results. Results of estimating Equation (4) are presented in Exhibit 9.

Exhibit 10 offers abbreviated goodness-of-fit results for all three specifications used in this article—Equations (1), (2), and (4)—as well as Wald specification tests for the three equations. Specifically, the specification tests are implemented as Wald tests for exclusion restrictions on the additional variables (Greene [2004]). That is, we start with the most comprehensive model as specified in Equation (4) and first test the null hypothesis that the coefficient a_1 on the *yearq* is equal to zero. Next, we test the joint exclusion restriction on the coefficients of all three variables that are not in the specification in Equation (1)—*DEBTFLOW, SPREAD*, and *yearq* (i.e., this tests H_0: $a_1 = a_6 = a_7 = 0$). In this sense, Equations (1) and (2) are nested with the comprehensive model in Equation (4) and the specification search can be conducted by testing these exclusion restrictions (Greene [2004]).

EXHIBIT 9

Multiple Regression Results (Extended Specification with Fixed Effects with Structural Change)

Independent Variable	Office	Industrial	Multifamily	Retail
Constant	0.568 (11.426)	0.683 (13.736)	0.530 (10.717)	0.639 (9.213)
Structural Change Term (OFC: 03q4, IND: 01q4, MFH: 01q2, RTL: 01q4)	–0.039 (–3.042)	–0.045 (–4.832)	–0.081 (–11.246)	–0.028 (–2.444)
Log(CAP)_{t-1}	0.522 (17.886)	0.482 (19.342)	0.566 (18.415)	0.423 (8.799)
Log(CAP)_{t-4}	0.187 (6.741)	0.189 (8.131)	0.157 (5.145)	0.226 (6.646)
$\text{Log(Real Rent Index)}_{t-s}$	–0.113 (–4.299)	–0.111 (–5.079)	–0.205 (–4.905)	–0.170 (–4.933)
Lag Length for RRI_s =	*2*	*4*	*0*	*4*
Real T-Bond 10-year	0.008 (2.294)	0.005 (2.217)	0.012 (3.820)	0.013 (3.305)
Risk Spread	0.064 (5.718)	0.053 (7.476)	0.044 (6.554)	0.096 (8.005)
Debt Flow	–0.398 (–5.469)	–0.333 (–5.363)	–0.229 (–3.996)	–0.266 (–3.041)
Q2	0.005 (0.641)	0.0003 (0.046)	–0.004 (–0.756)	0.005 (0.636)
Q3	–0.034 (–4.257)	–0.014 (–2.134)	–0.015 (–2.461)	–0.016 (–1.818)
Q4	–0.034 (–4.138)	–0.020 (–2.875)	–0.009 (–1.368)	0.018 (2.044)
R-square (adjusted)	0.613	0.558	0.840	0.581
Number of cross-sectional units (MSA markets)	38	38	34	27
Number of usable observations (excludes missing values)	2656	2948	1781	1903
Test of group significance of fixed effects	F(37,*) = 1.78283 Significance Level: 0.00236351	F(37,*) = 1.60289 Significance Level: 0.01140569	F(33,*) = 1.61919 Significance Level: 0.01366038	F(26,*) = 1.87666 Significance Level: 0.00436744

Notes: The dependent variable is Log(Cap). t-statistics are in parentheses. Estimate of fixed effects omitted for brevity. All data are quarterly from 1980 Q1 through 2007 Q4.

EXHIBIT 10

Goodness-of-Fit Statistics and Specification Tests

	Office	Industrial	Multifamily	Retail
Standard Rents and T-Bond Model				
Adjusted R^2	0.585	0.525	0.824	0.542
Sum of Squared Residuals	59.106	52.492	16.517	39.000
Log Likelihood	1284.663	1785.286	1640.872	998.839
Extended, No Structural Change				
Adjusted R^2	0.612	0.554	0.831	0.580
Sum of Squared Residuals	55.156	48.951	15.797	35.778
Log Likelihood	1376.519	1857.506	1680.581	1080.874
Extended with Structural Change				
Adjusted R^2	0.613	0.558	0.840	0.581
Sum of Squared Residuals	54.976	48.520	14.924	35.661
Log Likelihood	1380.846	1870.564	1731.177	1083.996
Specification Tests				
H_0: Coefficients on year Q, spread, debtflow jointly = 0	Chi-Squared(3) = 162.374313 or F(3,*) = 54.12477 with Significance Level 0.00000000 **Reject H_0**	Chi-Squared(3) = 164.132211 or F(3,*) = 54.71074 with Significance Level 0.00000000 **Reject H_0**	Chi-Squared(3) = 173.941320 or F(3,*) = 57.98044 with Significance Level 0.00000000 **Reject H_0**	Chi-Squared(3) = 124.261038 or F(3,*) = 41.42035 with Significance Level 0.00000000 **Reject H_0**
H_0: Coefficient on year Q = 0	Chi-Squared(1) = 9.251132 with Significance Level 0.00235350 **Reject H_0**	Chi-Squared(1) = 23.348792 with Significance Level 0.00000135 **Reject H_0**	Chi-Squared(1) = 126.465542 with Significance Level 0.00000000 **Reject H_0**	Chi-Squared(1) = 5.971269 with Significance Level 0.01454081 **Reject H_0**

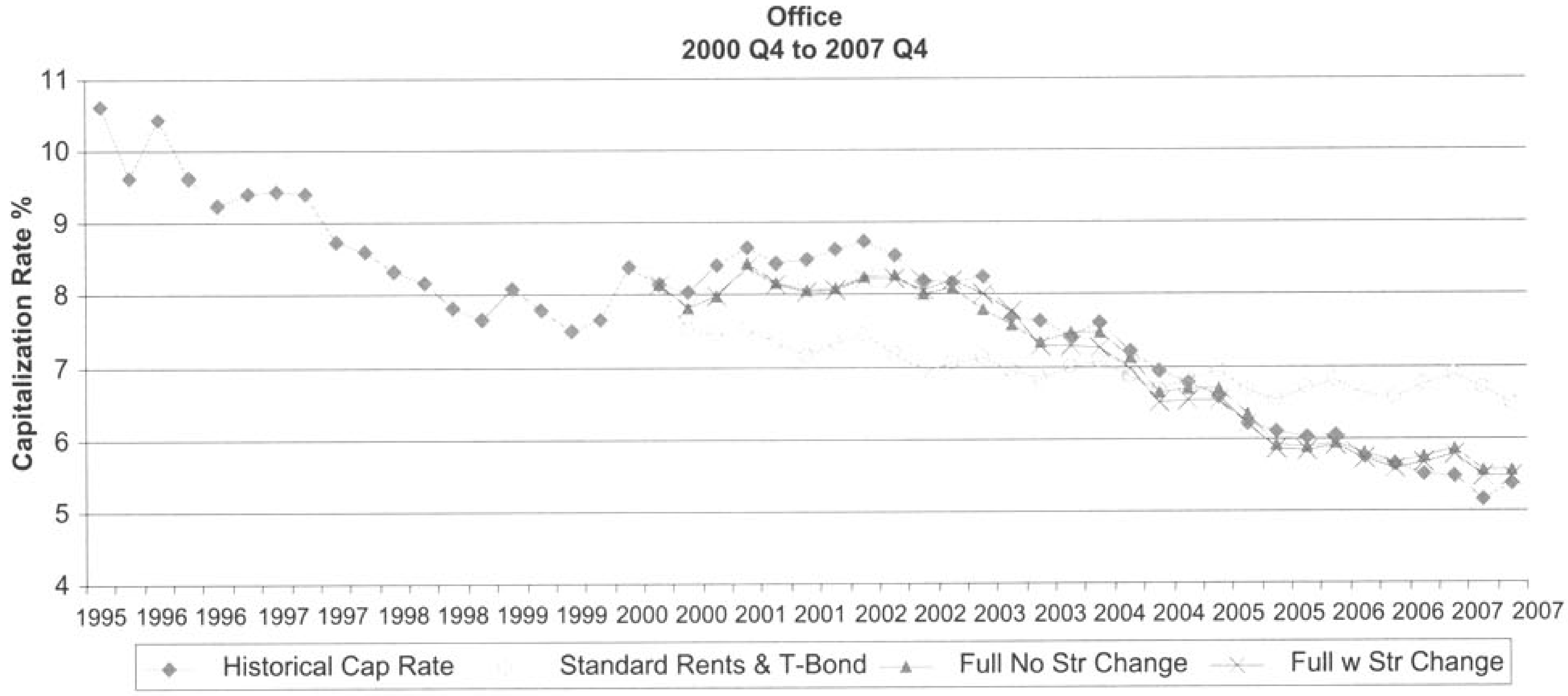
Exhibit 10 shows that the progression of specifications from Equation (1) to Equation (2) and to Equation (4) produces at each stage a statistically significant increase in explanatory power of the model. This is further confirmed by the goodness of fit statistics, such as the adjusted R-squared. The ranking testifies to the importance of such financial factors as debt availability and risk premiums in modeling capitalization rates, as well as accounting for long-run gradual structural change induced by changing investor sentiment.

BACKTESTS AND FORECASTING PERFORMANCE OF ALTERNATIVE SPECIFICATIONS

Although the goodness-of-fit tests are an important indicator of relative model performance, they are not always conclusive. Specifically, when lagged dependent variables are used, dynamic models customarily generate high measures of fit (and this is true in our case). It is often hard to judge between the various model specifications when they all exhibit such high measures of fit.

A complimentary approach to judge relative model performance is to construct a number of backtests in order to ascertain the ability and effectiveness of each model to explain the historical data. The backtests start at a point in the past and use the equation that was estimated on the full historical sample to dynamically forecast the dependent variable within a specified sample period. In this approach, the actual historical values for the model's exogenous right-side variables are used, but any autoregressive terms, such as the lagged cap rates, use the *previous period's forecast*; this procedure distinguishes a dynamic in-sample forecast from the more common predicted values of the model used in R^2 calculations. As a result, the process allows the researcher to compare the in-sample forecast to actual historical observations and to judge model performance. This method has an advantage over standard measures of fit in that it allows us to judge

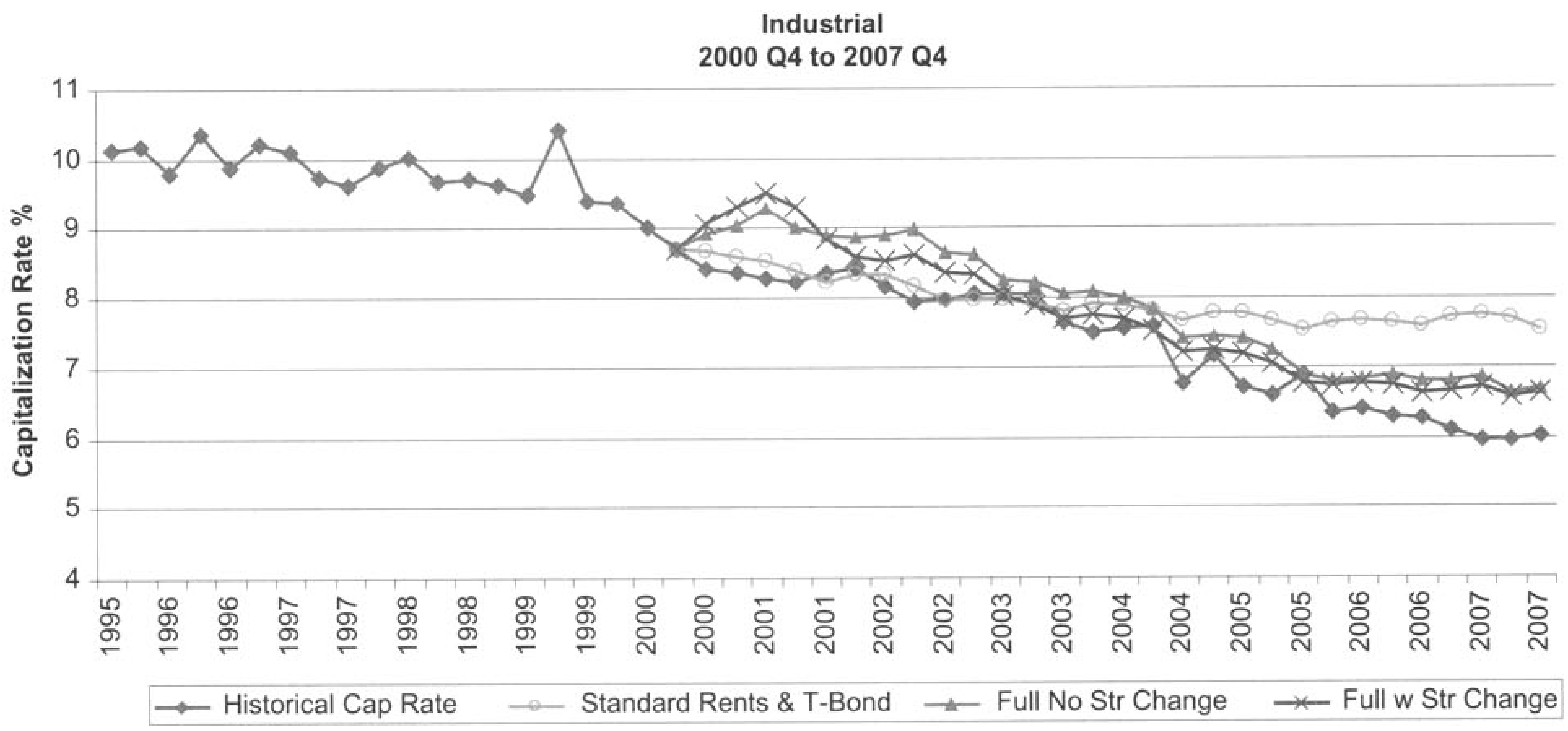
EXHIBIT 11
Backtesting Model Specifications



Backtest Forecasting Performance: Office

Model	Mean Error of Forecast	Mean Absolute Error of Forecast	Theil U
Standard Rents and T-Bond	–1.0979307	1.0979307	0.3964
Extended No Structural Change	–0.1829746	0.1829746	0.0661
Extended with Structural Change	–0.1109782	0.1109782	0.0401

Based on 29 forecast steps from 2000 Q4–2007 Q4.

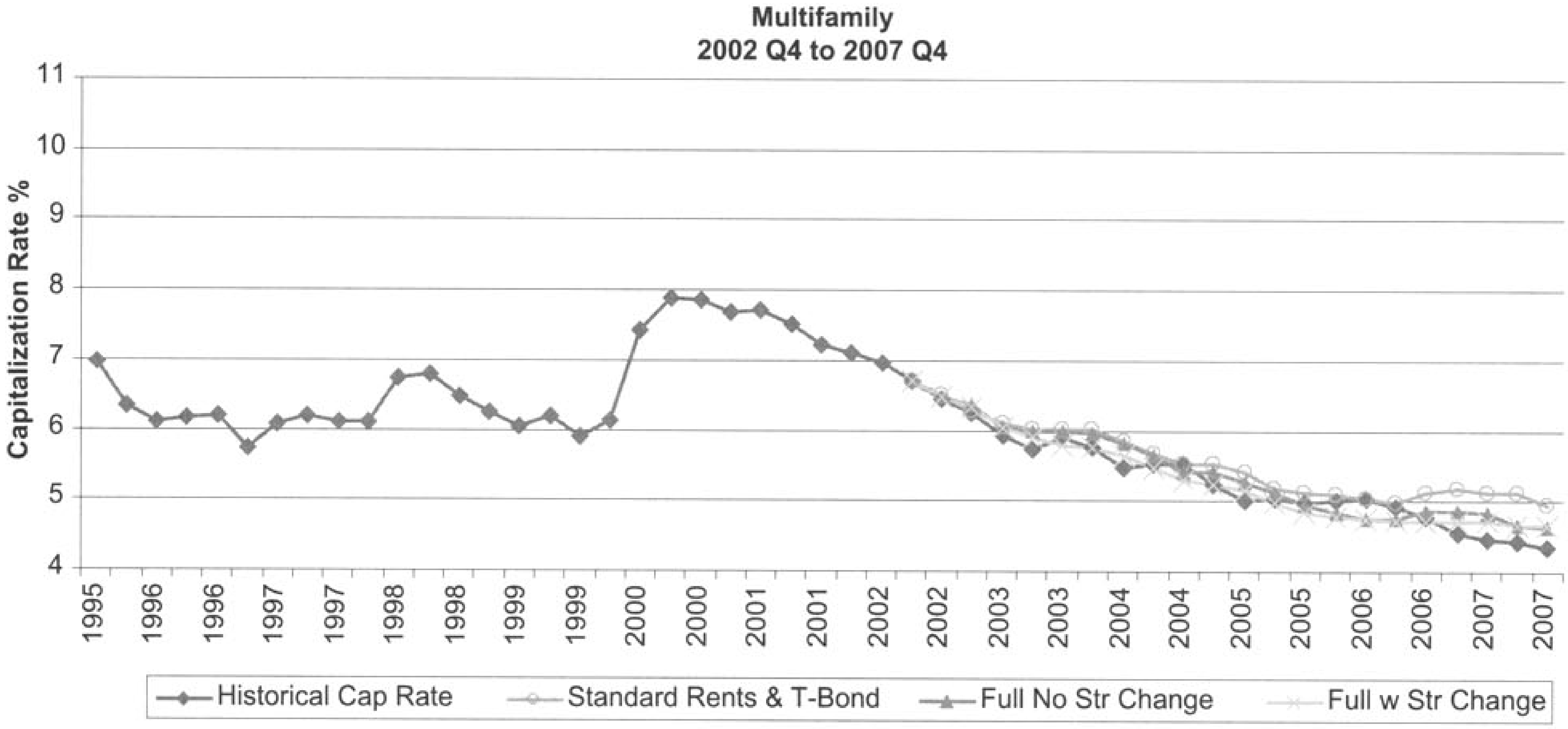


Backtest Forecasting Performance: Industrial

Model	Mean Error of Forecast	Mean Absolute Error of Forecast	Theil U
Standard Rents and T-Bond	–1.5101044	1.5101044	0.5611
Extended without Structural Change	–0.6815805	0.6815805	0.2532
Extended with Structural Change	–0.6245786	0.6245786	0.2321

Based on 29 forecast steps from 2000 Q4–2007 Q4.

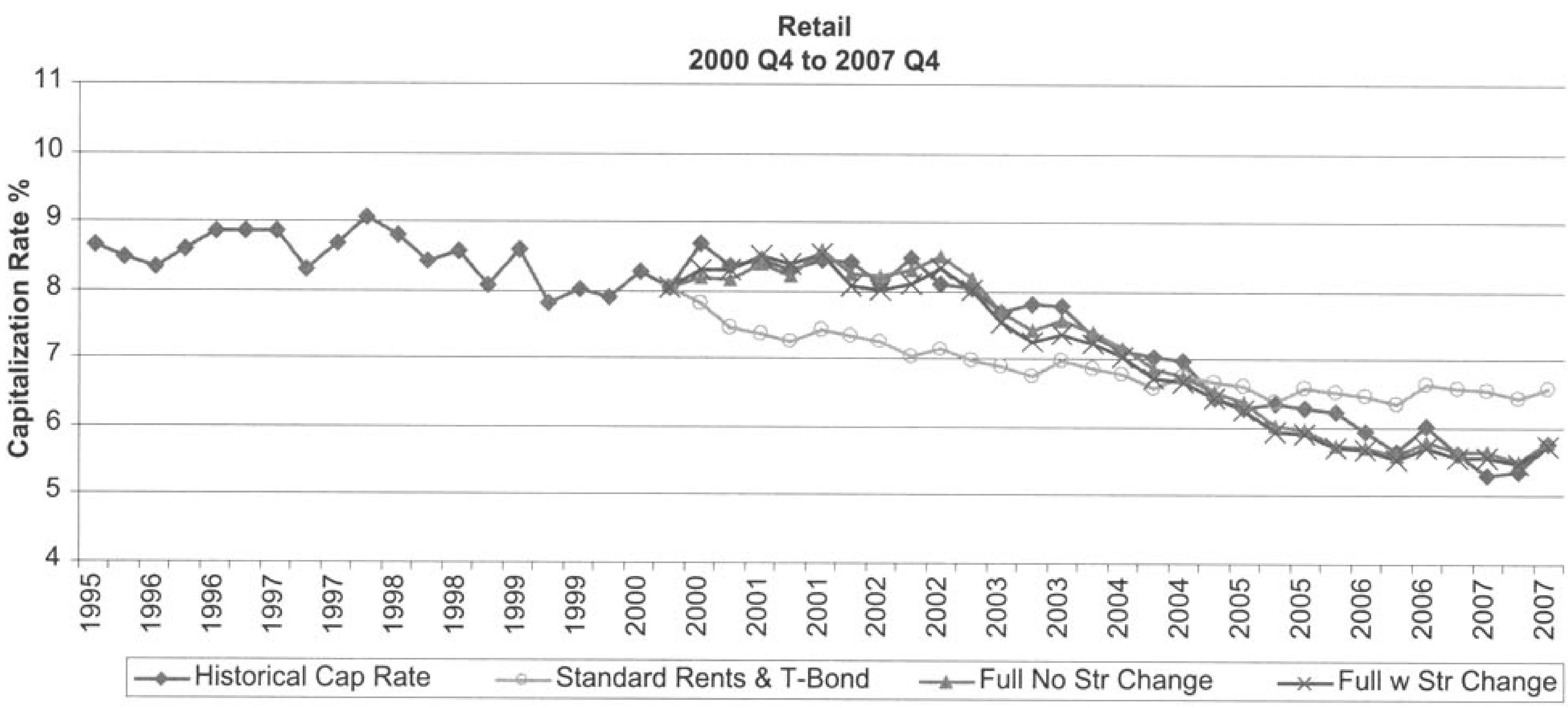
Exhibit 11 (*Continued*)



Backtest Forecasting Performance: Multifamily

Model	Mean Error of Forecast	Mean Absolute Error of Forecast	Theil U
Standard Rents and T-Bond	–0.6753247	0.6753247	0.2975
Extended No Structural Change	–0.2254044	0.2254044	0.0993
Extended with Structural Change	–0.214616	0.214616	0.0945

Based on 20 forecast steps from 2002 Q4–2007 Q3.



Backtest Forecasting Performance: Retail

Model	Mean Error of Forecast	Mean Absolute Error of Forecast	Theil U
Standard Rents and T-Bond	–0.8105259	0.8105259	0.3526
Extended No Structural Change	–0.0228433	0.0228433	0.0099
Extended with Structural Change	0.0087957	0.0087957	0.0038

Based on 29 forecast steps from 2000 Q4–2007 Q4.

how well the different models can replicate historical data. The emphasis in the backtests is on the ability of the various model specifications to replicate the strong decline in cap rates experienced across property types (often dubbed "cap-rate compression") in the period from 2000 to 2007.

Exhibit 11 shows the backtest results for all three models described in this article as well as performance statistics and the graphs of backtest forecasts. All backtests are performed against historical cap rates by using the model estimated on the entire sample to dynamically forecast capitalization rates from 2000 Q4 through the end of the sample in 2007 Q4 using historical data for the independent variables.[4] These dynamic forecasts are performed in a panel setting, which generates a cap rate forecast for each cross-sectional MSA unit. Next, these individual MSA forecasts are dynamically weighted by real estate stock in each market to produce a national weighted average forecast.[5] Finally, the weighted national forecast is used in conjunction with the historical weighted-average cap rate (also dynamically weighted by stock) to produce various forecast performance statistics reported for each model specification. These statistics, together with backtest plots, allow us to judge the relative success of the three models in explaining historical capitalization rates.

The standard (first) specification performs the worst in explaining historical capitalization rates. Specifically, the examination of the backtest plots for this model against historical data shows that the model does a poor job of explaining the cap-rate compression over the period 2000–2007 for all property types, except possibly multifamily housing. In contrast, the extended version of the model, which accounts for debt availability and economy-level risk, shows a marked improvement in explaining historical cap rates. Using the Theil test, the addition of these variables makes a significant reduction in forecast error over the period 2000 Q4–2007 Q4.

Finally, the model in Equation (4) with structural shift terms performs the best among all three tries described in this article, although the incremental improvement of the extended specification with structural change is not as strong as the incremental improvement garnered by adding the risk premium and debt availability factors. Overall, results of these in-sample backtests confirm the model performance ranking of the previous section; there is still evidence of structural change even after the critically important addition of the macroeconomic financial factors of debt availability and risk premium.

CONCLUSION

The slowly meandering pattern of structural change that is detected with the CUSUM analysis tends, at least in part, to follow the profile of the business cycle. If we interpret the structural changes as being investor sentiment, the pattern is a build-up of positive sentiment until a recession followed by a period of negative sentiment. This was certainly the case with the panic-style asset underpricing in the middle of the recession in the late 1980s and early 1990s and the subsequent real estate crisis.

Interestingly, this pattern does not occur in and around the 2001 recession. Rather, at the end of that recession, sentiment turned very positive and continued through the end of 2007, just before the beginning of the current financial crisis. This period is generally referred to in the real estate industry as the "great cap-rate compression." Some authors (see Caballero, Farhi, and Gourinchas [forthcoming]) have argued that a flood of global capital increased the availability of debt over the last decade, which in turn had the effect of pushing up asset prices and creating asset "bubbles." That hypothesis is consistent with our CUSUM results, but we must remember that our model already includes a variable that explicitly incorporates the availability of debt. That measure does show a large expansionary period of debt—peaking in 2007—consistent with the global imbalances hypothesis. But our results support the idea that something additional was happening at that time—perhaps a true shift in real estate investor sentiment.

APPENDIX

Statistical Summary of Variables

Because the time period differs between property type (except for office and industrial), the moments for national variables and the number of included observations also differ.

Variable	Obs	Mean	Std Error	Minimum	Maximum
Office					
Log(CAP)	2814	2.012677	0.234099	0.686123	2.762589
Log(Real Rent Index)	5382	−0.033678	0.157157	−0.619435	0.855274
Real T-Bond	5510	3.555497	1.797885	0.264329	9.100207
Risk Spread	5662	1.022259	0.404341	0.013333	2.27333
Debt Flow	5662	0.220033	0.058572	0.093652	0.352057
Industrial					
Log(CAP)	3175	2.064373	0.193181	1.122329	2.892148
Log(Real Rent Index)	5437	−0.02478	0.140474	−0.539366	0.555696
Real T-Bond	5510	3.555497	1.797885	0.264329	9.100207
Risk Spread	5662	1.022259	0.404341	0.013333	2.27333
Debt Flow	5662	0.220033	0.058572	0.093652	0.352057
Multifamily					
Log(CAP)	1920	1.921208	0.235038	0.712165	2.554744
Log(Real Rent Index)	4099	0.003288	0.082049	−0.256498	0.319933
Real T-Bond	4930	3.555497	1.797904	0.264329	9.100207
Risk Spread	5066	1.022259	0.404345	0.013333	2.27333
Debt Flow	5066	0.220033	0.058573	0.093652	0.352057
Retail					
Log(CAP)	2011	1.980214	0.215791	0.337044	2.796623
Log(Real Rent Index)	3798	−0.014735	0.142909	−0.749771	0.458475
Real T-Bond	3834	3.563226	1.809565	0.264329	9.100207
Risk Spread	3942	1.032945	0.399909	0.013333	2.27333
Debt Flow	3942	0.221487	0.058235	0.093652	0.352057

MSAs Used in the Panel

Office	Industrial	Multifamily	Retail
Atlanta	Atlanta	Atlanta	Atlanta
Austin	Austin	Austin	Austin
Baltimore	Baltimore	Baltimore	Baltimore
Boston	Boston	Boston	Boston
Charlotte	Charlotte	Charlotte	Chicago
Chicago	Chicago	Chicago	Columbus
Columbus	Cincinnati	Cincinnati	Dallas
Dallas	Columbus	Dallas	Denver
Denver	Dallas	Denver	Fort Lauderdale
Detroit	Denver	Fort Lauderdale	Houston
Edison	Edison	Fort Worth	Los Angeles
Fort Lauderdale	Fort Lauderdale	Houston	Miami
Houston	Fort Worth	Kansas City	Minneapolis
Kansas City	Houston	Las Vegas	New York

APPENDIX (*Continued*)

MSAs Used in the Panel			
Office	**Industrial**	**Multifamily**	**Retail**
Los Angeles	Indianapolis	Los Angeles	Oakland
Miami	Kansas City	Memphis	Orange County
Minneapolis	Los Angeles	Miami	Orlando
New York	Memphis	Minneapolis	Philadelphia
Newark	Miami	Nashville	Phoenix
Oakland	Minneapolis	New York	Portland
Orange County	New York	Orange County	Sacramento
Orlando	Oakland	Orlando	San Diego
Philadelphia	Orange County	Philadelphia	San Francisco
Phoenix	Orlando	Phoenix	San Jose
Pittsburgh	Philadelphia	Portland	Seattle
Portland	Phoenix	Raleigh	Washington, DC
Raleigh	Portland	Riverside	West Palm Beach
Sacramento	Riverside	Salt Lake City	
San Antonio	Sacramento	San Diego	
San Diego	Salt Lake City	Seattle	
San Francisco	San Diego	St. Louis	
San Jose	San Francisco	Tampa	
Seattle	San Jose	Washington, DC	
St. Louis	Seattle	West Palm Beach	
Stamford	St. Louis		
Tampa	Tampa		
Washington, DC	Ventura		
West Palm Beach	Washington, DC		
38 Markets	**38 Markets**	**34 Markets**	**27 Markets**

ENDNOTES

[1]Real estate capitalization rates can be thought of as inverse price/earnings ratios.

[2]As before, there are individually significant MSAs for each property type.

[3]We ran a battery of additional tests to confirm these dynamics. Specifically, we ran CUSUM tests with iteration starting in 1998 Q1 that formally confirmed a statistically significant downward trend in CUSUMs in recent years. Alternatively, we utilized graphs from recursive coefficient tests (forecast errors) without summing them, along with +/− 2 standard error bands. This approach helped pinpoint specific dates when prediction residuals were significantly different from zero (Dinardo and Johnston [1996]) and confirmed the story told by CUSUMs. Both test results and related graphs are omitted for brevity.

[4]Backtest forecasts for multifamily start in 2002 Q4 due to issues around the year 2000 with the averaged national series for multifamily.

[5]The stock measure used is thousands of square feet in each market for the given property type. The weighting is dynamic in that for each time period t, that period's stock series is used across the cross section to produce the national cap rate value for the period t.

REFERENCES

Archer, W.A., and D.C. Ling. "The Three Dimensions of Real Estate Markets: Linking Space, Capital, and Property Markets." *Real Estate Finance*, Fall 1997, pp. 7–14.

Baker, M., and J. Stein. "Market Liquidity as a Sentiment Indicator." *Journal of Financial Markets*, 7 (2004), pp. 271–299.

Baker, M., and J. Wurgler. "Investor Sentiment and the Cross-Section of Stock Returns." *Journal of Finance*, Vol. 61, No. 4 (2006), pp. 1645–1680.

——. "Investor Sentiment in the Stock Market." *Journal of Economic Perspectives*, 21 (2007), pp. 129–151.

Barberis, N., and R. Thaler. "A Survey of Behavioral Finance." Chapter 18 in *Handbook of the Economics of Finance,* Vol. 1, Part 2, edited by G. Constantinides, M. Harris, and R. Stulz, pp. 1053–1128. Amsterdam: Elsevier, 2003.

Brown, G., and M. Cliff. "Investor Sentiment and the Near-Term Stock Market." *Journal of Empirical Finance*, 11 (2004), pp. 1–27.

——. "Investor Sentiment and Asset Valuation." *Journal of Business*, Vol. 78, No. 2 (2005), pp. 405–440.

Brown, R.L., J. Durbin, and J.M. Evans. "Techniques for Testing the Constancy of Regression Relationships over Time." *Journal of the Royal Statistical Society*, Series B, 37 (1975), pp. 149–192.

Caballero, R., E Farhi, and P. Gourinchas. "An Equilibrium Model of Global Imbalances and Low Interest Rates." *American Economic Review,* forthcoming.

Chen, J., S. Hudson-Wilson, and H. Nordby. "Real Estate Pricing: Spreads and Sensibilities—Why Real Estate Pricing Is Rational." *Journal of Real Estate Portfolio Management*, 10 (2004), pp. 1–21.

Chichernea, D., N. Miller, J. Fisher, M. Sklarz, and R. White. "A Cross-Sectional Analysis of Cap Rates by MSA." *Journal of Real Estate Research*, Vol. 30, No. 3 (2008), pp. 10–29.

Chow, G.C. "Tests of Equality between Sets of Coefficients in Two Linear Regressions." *Econometrica*, Vol. 28, No. 3 (1960), pp. 591–605.

Clayton, J., D.C. Ling, and A. Naranjo. "Commercial Real Estate Valuation: Fundamentals Versus Investment Sentiment." *Journal of Real Estate Finance and Economics*, Vol. 38, No. 1 (2009), pp. 5–37.

Dinardo, J., and J. Johnston. *Econometric Methods*, 4th ed. McGraw-Hill/Irwin, 1996.

Fisher, J., D.C. Ling, and A. Naranjo. "Commercial Real Estate Return Cycles: Do Capital Flows Matter?" Working Paper, University of Florida/RERI, 2007.

Gallin, J. "The Long Run Relationship between House Prices and Income..." *Real Estate Economics*, Vol. 34, No. 3 (2006), pp. 417–439.

Geltner, D., N. Miller, J. Clayton, and P. Eicholtz. *Commercial Real Estate Analysis and Investments*, 2nd ed. South-Western Educational Publishing, 2007.

Ghysels, E., A. Plazzi, and R. Valkanov. "Valuation in U.S. Commercial Real Estate." *European Financial Management*, Vol. 13, No. 3 (2007), pp. 472–497.

Greene, W. *Econometric Analysis*, 5th ed. Englewood Cliffs, NJ: Prentice-Hall, 2004.

Han, A., and D. Park. "Testing for Structural Change in Panel Data: Application to a Study of U.S. Foreign Trade in Manufacturing Goods." *The Review of Economics and Statistics*, Vol. 71, No. 1 (1989), pp. 135–142.

Hansen, B. "The New Econometrics of Structural Change: Dating Breaks in U.S. Labor Productivity." *Journal of Economic Perspectives*, Vol. 15, No. 4 (2001), pp. 117–128.

Hendershott, P.H., and B. MacGregor. "Investor Rationality: Evidence from U.K. Property Capitalization Rates." *Real Estate Economics*, 26 (2005a), pp. 299–322.

——. "Investor Rationality: An Analysis of NCREIF Commercial Property Data." *Journal of Real Estate Research*, 26 (2005b), pp. 10–29.

Hirshleifer, D. "Investor Psychology and Asset Pricing." *Journal of Finance*, 56 (2001), pp. 1533–1597.

Kiyotaki, N., and J. Moore. "Credit Cycles." *Journal of Political Economy*, Vol. 106, No. 2 (1997), pp. 211–248.

Ling, D.C., and A. Naranjo. "The Dynamics of REIT Capital Flows and Returns." *Real Estate Economics*, 31 (2003), pp. 10–29.

——. "Dedicated REIT Mutual Fund Flows and REIT Performance." *Journal of Real Estate Finance and Economics*, Vol. 32, No. 4 (2006), pp. 409–433.

Maskus, K.E. "Evidence on Shifts in the Determinants of the Structure of U.S. Manufacturing Foreign Trade, 1958–76." *The Review of Economics and Statistics*, Vol. 65, No. 3 (1983), pp. 415–422.

Miller, M., and J. Stiglitz. "Leveraging and Asset Bubbles:..." Columbia University (Mimeo), November 2008.

Quandt, R. "Tests of the Hypothesis That a Linear Regression Obeys Two Separate Regimes." *Journal of the American Statistical Association*, 55 (1960), pp. 324–330.

Shilling, J.D., and T.F. Sing. "Do Institutional Real Estate Investors Have Rational Expectations?" Working Paper, 2007.

Sivitanides, P., J. Southard, R. Torto, and W. Wheaton. "The Determinants of Appraisal-based Capitalization Rates." *Real Estate Finance*, Vol. 18, No. 2 (2001), pp. 27–37.

Sivitanidou, R., and P. Sivitanides. "Office Capitalization Rates: Real Estate and Capital Market Influences." *Journal of Real Estate Finance and Economics*, Vol. 18, No. 3 (1999), pp. 297–322.

Wheaton, W. "Real Estate Cycles: Some Fundamentals." *Real Estate Economics*, Vol. 27, No. 2 (1999), pp. 209–230.

White, H. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and Direct Test for Heteroskedasticity." *Econometrica*, 48 (1980), pp. 817–838.