The Secular and Cyclic Determinants of Capitalization Rates: the Role of Property Fundamentals, Macroeconomic Factors, and Investor Sentiment

by

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Abstract

In this paper we revisit many studies that have attempted to explain the determinants of real estate capitalization rates. We introduce two new innovations. First we are able to identify two macroeconomic factors that greatly impact cap rates besides risk free treasury rates. These are the general corporate risk premium operating in the economy, and the amount of debt (liquidity) available. The addition of these factors greatly adds to the ability of previous models to explain the secular fall of cap rates in the last decade and the recent rise. In addition, we use innovative tests for "structural" shifts in the cap rate – even including all of these macro-economic factors. Our tests identify two distinct "periods" which we label "investor sentiment". These were a period of negative sentiment in 1991-1996 and a period of positive sentiment from 2002-2007.

Methodologically, our analysis uses a large and robust quarterly panel data set of 30 US metropolitan areas from 1980q1 through 2007q4. We compare models not only using traditional measures of within sample "fit", but also examine how the models behave in in-sample "back test" forecasts.

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I. Introduction

In this paper we revisit many studies that have attempted to explain the determinants of real estate capitalization rates. We introduce two new innovations. First we are able to identify two macroeconomic factors that greatly impact cap rates besides risk free treasury rates. These are the general corporate risk premium operating in the economy, and the amount of debt (liquidity) available. 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 recent rise during the "financial crisis". In addition, we use innovative tests for "structural" shifts in the cap rate – even including all of these macro-economic factors. Our tests identify two distinct "periods" which we label "investor sentiment". These were a period of negative sentiment in 1991-1996 and a period of positive sentiment from 2002-2007.

Methodologically, our analysis uses a large and robust quarterly panel data set of 30 US metropolitan areas from 1980q1 through 2007q4. We compare models not only using traditional measures of within sample "fit", but also examine how the models behave in in-sample "back test" forecasts. Our paper is organized as follows. In Section II we review the literature on cap rates as well as studies of investor sentiment. Section III details our panel data base and outlines the basic econometric model we use. We also present our results using models as they exist in the literature and then with our additional macroeconomic variables. In Section IV, we discuss a number of tests for structural shifts in cap rates. We call these periods of changing "investor sentiment". Sections V and VI compare the ability of the three models to explain changes in cap rates over the last 3 decades, both using within sample performance and in-sample back test forecasts. Section VII draws some Conclusions.

II. Background and Related Literature

The starting point of our paper is a long literature on real estate capitalization rates. A number of studies have modeled cap rates as an adjustment around equilibrium values, which are in turn are determined by real estate fundamentals such as rent levels and rental growth, as well as macro-level risk-free interest rates (see Sivitanides, Southard, Torto, and Wheaton (2001), Hendershott and MacGregor (2005a,b); Chen et al, (2004); Chichernea et al. (2008), Sivitanidou and Sivitanides (1999), Shilling and Sing (2007)). One of these studies also includes a metric for a general risk premium over the risk free rate (see Archer and Ling (1997)). Our paper draws on this literature in order to specify what we term as a standard, literature-based model, which emphasizes these fundamentals in determining capitalization rates. We specifically draw on Sivitanides, Southard, Torto, and Wheaton (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,b), Ghysels, Plazzi, and Valkanov (2007)).

To this literature we add the idea that macro economic capital flows and the availability debt may also impact capital pricing. In the literature, there are theoretical models of asset pricing in which capital flows play an obvious role (for example Geltner et al (2007), Wheaton (1999)). Empirically, some recent work on real estate returns has begun to include the dynamics of commercial real estate capital flows (Ling and Naranjo (2003, 2006) as well as Fisher et al. (2007)). These studies find that capital flows into public (securitized) markets do not predict subsequent returns, but at the same time returns affect subsequent capital flows into these real estate markets (Ling and Naranjo (2003, 2006)). Furthermore, there is evidence that lagged institutional capital flows have an effect on current returns at the aggregate level (Fisher et al. (2007)).

This paper is also related to the general finance literature in that it draws on the idea of investor sentiment from behavioral finance. This behavioral framework posits that since investors are not purely rational in their decision-making process, systemic biases in investors’ beliefs will cause them to make trading decisions on non-fundamental information, which is typically referred to as sentiment. Specifically, Baker and Wurgler (2007) offer a definition of investor sentiment as a biased belief about the future growth rate of cash flows and investment risks based on the present information set. As Clayton, Ling, and Naranjo (2009) explain, this sentiment-driven mispricing of assets is further augmented by “limits to arbitrage” in that non-trivial transaction and implementation costs prevent arbitrageurs from taking fully offsetting positions to correct mispricing. These transaction costs are especially high in the real estate sector and are further exacerbated by short-selling constraints on real estate assets. The interplay between sentiment (with the attendant limitations on efficient fundamentals-based pricing) and fundamental factors, therefore, is an important determinant of real estate asset prices and must be analyzed to understand asset valuation.

In terms of short-sale constraints, Baker and Stein (2004) provide an insightful analysis of pricing under short selling limitations. Specifically, in the presence of short-selling constraints, 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.

A related literature uses microeconomic analysis of investor psychology to explain investors’ reaction to past returns and information, with the emphasis on irrational under or over-reaction tendencies. Hirshleifer (2001), as well as Barberis and Thaler (2003), offer comprehensive reviews of that literature. Similarly there are empirical studies of investor sentiment about stock returns. Most of these studies employ principal component analysis along with some form of sentiment proxies to ascertain the potential influence of sentiment. Papers of note include Brown and Cliff (2004, 2005) and Baker and Wurgler (2006, 2007).

We should also note at this point the emergence of an additional thesis in macroeconomics regarding the general increase in asset prices observed in the last 10-15 years. This thesis postulates that due to the heterogeneity in countries' ability to produce financial assets for global savers, large capital flows from developing countries to developed ones have become manifest in the last 10-15 years, the process dubbed "global imbalances" (see Caballero et al (2008)). These capital inflows, the argument goes, have tremendously increased debt availability in the US economy and have bid up asset prices across the board, including those of real estate assets. This idea is difficult to distinguish empirically from a period of "investor sentiment" and we discuss this hypothesis in the light of our estimation results and structural change tests later in the paper.

Our paper is most closely related to the recent work by Clayton, Ling, and Naranjo (2009). In this insightful paper, the authors use an error-correction specification to model national-level cap rate dynamics and examine the extent to which fundamentals and investor sentiment help to explain the time-series variation in national-level cap rates. They find evidence of significant impact of sentiment on pricing, even after controlling for such factors as changes in expected rental growth, risk premiums, T-bond yields, and lagged adjustment from long-run market equilibrium. Our innovation is to use a much larger panel data base, as well as incorporating a direct measure of liquidity and debt availability.

III. Data and Methodology: basic models

We begin by using two models to analyze capitalization rates. The first one is based on the approaches used in the literature so far, which emphasize local real estate fundamentals as well as an economy-level interest rate in modeling capitalization rates. The second model extends this first one by adding variables to account for an economy wide risk premiums and the general availability of debt. Both of these variables are measured for the economy as a whole – to avoid problems of endogeneity.

All of our models are estimated separately for each type of real estate (e.g. office, retail, etc.). For each we use an unbalanced panel (they contain missing values for some observations) that spans the period from 1980 q1 to 2007 q4 with quarterly data, for over 30 MSA markets (for a statistical summary of the data set, see Appendix). As a result, in spite of missing values, the dataset contains upward of 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 paper are estimated using the fixed effects panel method (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 the time-series as well as cross-sectional (between various MSA's) variation, which increases the efficiency of the OLS estimator (see Greene (2004)) and generates better estimates of model coefficients. Furthermore, it 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 test for their statistical significance. Finally, the higher estimator efficiency increases the power of post-estimation tests, which allows for better inferences about results. Table 1 lists all variables used in this paper as well as their sources. The statistical summary for these variables is given in the Appendix.

As can be seen from Table 1, the Real Rent Index is the only right-hand-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, since these would cancel out the effect of national macroeconomic variables.

Standard Literature-Based Specification: Rents and Treasury Yields

The first, most basic model intends to reflect the standard approach used in the literature so far (for reference see Sivitanides, Southard, Torto, and Wheaton (2001), on which the first specification is based). It postulates cap rates as an adjustment process around equilibrium values. The equilibrium is determined by two sets of influences: 1) the influences of discount rate that reflect both the opportunity cost of capital and systematic market risk; (2) factors that shape investors' income growth expectations. This is in keeping with the literature, which usually uses rental fundamentals and some proxy for interest rate to explain cap rates.

As discussed above, the standard specification we use is given in (1). It is formulated so as to be comparable to more extended specifications used below.

$$Log(C_{j,t}) = a_0 + a_1 log(C_{j,t-1}) + a_2 log(C_{j,t-4}) + a_3 log(RRI_{j,t}) + a_4 RTB_t + a_7 Q2_t + a_8 Q3_t + a_9 Q4_t + a_{10} D_j \qquad (1)$$

This is a panel specification where *j* is Metropolitan Statistical Areas (MSA) and *t* is time. This is 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.

$RRI_{j,t}$ This is real rent index calculated as a ratio of real rent data from Torto Wheaton rent database for a given MSA in a given quarter to the historical average of real rent for this MSA:

$$RRI_{j,t-s} = Real\ Rent_{j,t} / Mean(Real\ Rent_j) \qquad (1.1)$$

where the mean is calculated over sample time period for each *j*.

RTB_t Real T-Bond yield calculated as nominal yield minus inflation rate; this proxies risk-free rate and the opportunity cost of capital.

$Q2_t$, $Q3_t$, $Q4_t$, Seasonal dummies to take out 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*, on the other hand, is theoretically ambiguous (see Sivitanides, Southard, Torto, and Wheaton (2001)) and depends on whether investors are forward or backward-looking. In 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 a downward adjustment is in order, causing them 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, Southard, Torto, and Wheaton (2001)), investors will project current rent growth into the future and will bid up asset values accordingly. 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.

Table 2 depicts estimation results for this basic model on our data set. 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, Southard, Torto, and Wheaton (2001).

The group effects test on MSA dummies yields insignificant statistics for all property types but retail, while individual tests show that some MSAs are significant, while others are not. This is in line with findings in Sivitanides, Southard, Torto, and Wheaton (2001), indicating that some markets exhibit statistically significant differences in average cap rate levels.

Extended Model Specification: Debt Flow and Risk Premium

In this specification, we attempt to improve on the existing literature by including two new variables. The first of these 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 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, as risk increases commensurately. But real estate is a very illiquid asset and debt provides purchase liquidity. Thus when debt is scarce, real estate transactions are more difficult and prices might be expected to fall (cap rates rise). In addition to the rent fundaments and risk-free interest rates commonly included in standard models, these two new factors theoretically could play an important role in the determination of cap rates.

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

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

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

$RRI_{j,t-s}$ Same as in (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.

$DEBTFLOW_t$ This variable captures the overall availability of debt in the economy, and is 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):

$$DEBTFLOW_t = Total\ Net\ Borrowing\ and\ Lending_t / GDP_t \quad (2.1)$$

The *Net Borrowing and Lending* is a flow variable which shows the net change in the amount of debt in the US economy over a give quarter. It covers all debt, and not just (final) consumer debt. As such it partly measures changes in the degree of financial intermediation. It is scaled by GDP to account for the size of the economy.

The expected coefficient signs for the variables carried over from (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 NOI stream). *DEBTFLOW*, on the other hand, is expected to have a positive effect on asset values as, *ceteris paribus* investors will 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 where 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 standard model (1). Results of estimating the extended model (2) are given in Table 3. It is interesting that all coefficients have the expected sings 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 4 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. Finally, unlike in the case of (1), group tests on the significance of MSA's indicate group significance for all property types except multifamily[1].

A comparison of estimation results of equation (1) and (2) show a marked improvement in the performance of the extended specification (2) vis-à-vis the standard version (1), across all property types. The extended model results in higher adjusted R squared statistics, which testifies to improved fit of the extended model (for details on goodness-of-fit see below). 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 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 risk premium demanded by investors have strong effects on real estate asset pricing, and omitting these factors in cap rate models has been a major deficiency in the literature so far. As such, equation (2) offers an improvement over the existing literature on modeling capitalization rates.

IV. Investor Sentiment and Structural Change

Even with the addition of debt flow measure and risk premium, the task of explaining cap rates is not necessarily finished. While these new variables capture aspects of investor preferences and liquidity more generally, we still have no measure of investor sentiment towards real estate as an asset class. Real estate is different than financial assets, partly because of its physicality, and partly because of the leasing structures which underlie its income stream. The relationship between market rent and the 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.

There is an understandable scarcity of studies looking at these effects, since ascertaining and measuring these forces is very difficult. The difficultly in deriving a measurement of investor sentiment as well as its likely gradual rate of change, make it understandably hard to incorporate in an econometric model. Hence, these factors are typically not included in standard approaches to analyzing cap rates and end up in the residuals, where of course they may generate systematic specification errors.

Our approach to estimating 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 and 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, which as discussed below, is uniquely suited to this task. This approach takes the best specification so far (2) as a baseline model and assumes there are gradually changing exogenous factors, which are responsible for long-run gradual structural change in this model. CUSUM tests, based on recursive estimation, are then used to test for the existence and timing of this long-run structural change.

Structural Change Tests

Since the CUSUM tests operate only in the time dimension, they can use up degrees of freedom. Since the MSA fixed effects are often insignificant individually, we have chosen to eliminate them for the CUSUM testing. This simplified version (omitted MSA-specific fixed effects) becomes effectively a pooled OLS specification (see Greene (2004) for pooled OLS estimator)), but is otherwise identical to model (2) described above. Results for estimating this simplified benchmark model are given in Table 4. As can be seen, all coefficients are significant and of the same sign as before and have magnitudes similar to results for (2). As such, (3) is a good benchmark model to be used with CUSUM tests. It is important to note that results for model (3) shown in Table 4 is equivalent to the last stage in recursive regressions used in tests below (since the last stage is estimated on the full sample of data).

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

Having specified the baseline model (3), this model in turn is used in recursive regression-based structural change tests. Specifically, we use the panel version of the cumulative sums test, originally developed by Brown, Durbin, and 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 (see Appendix for details). After performing CUSUM tests, we further extend the analysis by plotting out the path of recursive model coefficients (as well as their standard error bands). This approach looks at what variables might be responsible for structural change, or whether it is a general factor external to the model (Dinardo and Johnston (1996)).

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

Figure 1 plots the CUSUM, along with the associated 10% significance bands. This set of recursive CUSUM's is based on iterations starting in 1987q1 (1988q1 for multifamily) and is shown. As can be seen from the plots, for all property types, the model under forecasts in the early 90's, with statistically significant structural change around 1991. This is evident from the CUSUM plots crossing the upper significance band during that period (significantly positive CUSUM values indicated that cap rates have become constituently higher than the ones predicted by the model, which can be interpreted as negative "investor sentiment". Subsequently, across all property types, CUSUM's begin to decline by the late 90's and early 2000's—the process reverses, and, the process again passes the 10% significance band (except office). This indicates under forecasting or positive "investor sentiment"[2].

Another interesting feature 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 start deviation from the 0 line mean. This means that models with shorter sample will not capture this gradual shift. Other tests for structural change (see Appendix for discussion of alternative tests) which are designed to detect radical shifts in relationships preceded and followed by long periods of stability (e.g. rolling dummy tests by Quandt (1960)) will not capture this dynamic either.

Before drawing conclusions as to the nature of this structural change, we graph recursively-estimated coefficients of the model with their 2 standard error bands in Figure 2. This is a useful technique to detect whether any structural change could be attributed to a particular variable. The interpretation of these is that if a coefficient (along with the error bands) moves radically from its previous trend, then there is structural change (Johnston (1996)). As can be seen from the graphs, the coefficients generally start out by being not significantly different from zero and then meander towards their expected statistically significant values as the recursive model picks up observations. They do not exhibit any radical shifts. This fact, coupled with the long periods of time it takes the CUSUM statistics to reach significance bands, indicates that the CUSUM profiles trace out gradually-occurring structural change that is 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 paper.

V. Comparative Analysis of Specifications

In light of these findings on the existence of gradual changes in model structure, the natural step is to extend model (2) further by explicitly accounting for structural change and test whether this model performs better in explaining capitalization rates than the previous approaches in equation (1) and (2). We accomplish this by adding a structural change dummy variable (a time dummy implying a change in the constant; see Chow (1960)) to specification (2). This dummy is designed to capture the cap rate structural change identified in the CUSUM analysis during the 2000-2004 period. While an imperfect device for modeling gradually occurring structural shifts, it is nonetheless useful for testing whether accounting for these shifts improves model performance. The resulting specification is:

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

Term *yearq* is the relevant structural shift dummy variable. The timing of the structural shift has been 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, since as shown by CUSUM tests this change is gradual and any single date would at any rate be arbitrary. The important condition is that the extended model includes a significant factor for structural change in the relevant time period (2000-2004), and this specification can in turn be used for comparison with the earlier results. Results of estimating (4) are presented in Table 5.

Table 6 offers abbreviated goodness-of-fit results for all three specification used in this paper used (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 (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 on all three variables that are not in specification (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 (4) and the specification search can be conducted by testing these exclusion restrictions (Greene (2004)).

As can be seen from Table 6, the progression of specifications from (1) to (2) and to (4) at each stage produces 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. This 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.

VI. Back-Tests and Forecasting Performance of Specifications

While goodness-of-fit tests utilized above are an important indicator of the relative model performance, they are not conclusive. Specifically, in a setting where lagged dependent variables are used, dynamic models customarily generate high measures of fit (for obvious reasons, including a lagged dependent variable has strong explanatory power), and it is hard to judge between the various specifications with such high measures of fit.

An alternative approach to judge the relative model performance is to construct a number of back-tests to ascertain the fit of each model and its effectiveness in explaining historical data. Such back-tests start at a point in the past and use the equation estimated on the full historical sample to dynamically forecast the dependent variable within the sample period using historical data for the right-hand-side variables (with the exclusion of autoregressive terms such as our lagged cap rates, which use previous period's forecast; this makes it a dynamic in-sample forecast). The result of this process allows the researcher to compare the in-sample forecast to actual historical observations and judge model performance. This method has an advantage over standard measures of fit in that it allows us to judge how well the different models can replicate historical data. The emphasis our back-tests is on the ability of the various specifications to forecast the strong decline in cap rates experienced across property types (dubbed the cap rate compression) in the period from 2000-2004.

Figure 3 shows the back-test results (both performance statistics and the graphs on back-test forecasts) for all 3 models used in this paper. All back tests are performed against historical cap rates by using the model estimated on the entire sample to dynamically forecast capitalization rates from 2000q4 through the end of the sample in 2007q4 using historical data for the independent variables[3]. 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[4]. Finally, this weighted national forecast is used in conjunction with the historical weighted average cap rate (also dynamically weighted by stock[3]) to produce various forecast performance statistics reported for each model specification (details on forecast performance statistics are included in the Appendix). These statistics, together with back-test plots, allow us to judge the relative success of the three models in explaining historical capitalization rates.

As can be seen from the graphs and forecast performance statistics, the standard specification performs the worst in explaining historical capitalization rates. Specifically, the examination of the back-test plots for this model against historical data shows that the model does a poor job of explaining the cap rate compression over 2000-2007. This suggests that the current standard approach used in the literature is inadequate in explaining a major part of recent cap rate variation. On the other hand, the extended version of the model, which accounts for debt availability and economy-level risk, shows a marked improvement in explaining historical cap rates.

Finally, model (4) with structural shift terms performs the best among all three tries in this paper, although the improvement on the extended specification without structural change (2) is not as drastic as the improvement of (2) over (1), which adds the risk premium and debt availability factors. These results further confirm the findings indicated by CUSUM tests that gradually-occurring structural change due to long-term hard-to-measure factors such as investor sentiment have an important effect on the dynamics of capitalization rates. Overall, results of these in-sample back-tests confirm the model performance ranking of the previous section, once more testifying to the importance of both financial factors such as debt and risk premiums as well as investor sentiment.

VII. Conclusion

The slowly evolving pattern of structural change that is detected with the CUSUM analysis tends at least partially to follow the profile of the business cycle. There is generally a build up of "positive sentiment" until a recession – after which there is "negative sentiment". This was certainly the case with the panic-style asset under pricing in the late 80's-early 90's in the middle of that recession 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 turns very positive and continues through the end of 2007, right before the beginning of the current financial crisis. This a period generally referred to in the real estate industry as the "great cap rate compression". Some authors (see Caballero (2008)) 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 created asset bubbles. While this hypothesis is consistent with our CUSUM results, 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 – a true shift in real estate investor sentiment.

Our evidence of slowly occurring hard-to-detect structural change demonstrates that exogenous factors, which are not part of standard econometric models used to analyze asset pricing in general can play a crucial role in cap rate behavior. While in and of itself not offering formal proof, this finding lends credence to the additional thesis regarding changes in real estate asset pricing discussed earlier (see literature review section). Also, our findings highlight the danger of assuming no structural change when estimating cap rate models spanning long periods of time. While doing so with panels over short time periods, where most variation is of cross-sectional type, might be warranted, ignoring structural change over the longer-term might result in model misspecification error and biased or inconsistent estimators. These results call for further research on the effect of long-term hard-to-measure factors—such as investor sentiment or shifts in global capital flows—on capitalization rates, both in terms of measuring these effects, as well as incorporating them into theoretical models.

Notes:

1. As before, there are individually significant MSA's for each property types; see Appendix for details
2. The authors have run a battery of additional tests to confirm these dynamics. Specifically, we have run CUSUM tests with iteration start in 1998q1, which formally confirmed that there is a statistically significant downward trend in CUSUMS in recent years. Alternatively, the authors have utilized graphs of recursive (forecast errors) without summing them, along with +- 2 standard errors bands. This helps pinpoint specific dates when prediction residuals were significantly different from zero (Dinardo and Johnston 1996); these confirmed the story told by CUSUMs. Both test results and related graphs are omitted for brevity.
3. Back-test forecasts start in 2002q4 for multifamily due to some issues with the averaged national series for multifamily around 2000.
4. The stock measure used in 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 this period *t*

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APPENDIX

Modified CUSUM Test Statistic

General Discussion

Here we explain in non-technical terms how the modified CUSUM test statistic works and also give reasons for the choice of this particular test over other structural change approaches available in the literature. The following subsection provides the mathematical details for the test.

Specifically, we use the panel version of the cumulative sums test, originally developed by Brown, Durbin, and Evans (1975). The panel version of the test follows the Maskus (1983) approach. This method is also one of the approaches utilized in Han and Park (1989). 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 further extend the analysis by plotting out the path of recursive model coefficients (as well as their standard error bands). This approach looks at what variables might be responsible for structural change, or whether it is a general factor external to the model (Dinardo and Johnston (1996)).

It is important to note the reason for the use of CUSUM structural change test, and not of other tests available in the literature. There are three main attractions of the CUSUM approach. First, it does not require a specification of the source of structural change in the form of one of the variable coefficients or the constant, as would be the case in Chow structural break tests, as well as more sophisticated tests derived from that approach. Second, unlike most other tests (including Chow (1960)), the CUSUM approach detects gradually-occurring continuous structural change. Most other tests assume a sharp adjustment in the structure preceded and followed by periods of stability in the model structure and simply will not detect the slow structural shifts. Finally, other testing approaches (for example Quandt's (1960) log-likelihood statistic, and other rolling time series tests as discussed in Hansen (2001)), do not have simulation-based critical values for the application of those tests in a panel regression setting. The work that has been done is confined to critical values for univariate time series analysis (see discussion of the Quandt statistic in Hansen (2001)). The CUSUM method employed in the paper, on the other hand, has known statistical properties, which allow the calculation of significance bands.

Following Maskus (1983), the essence of the CUSUM test is as follows (the mathematical details are included in the Appendix). The test is based on recursive estimation: the addition of a vector of cross-sectional observations for each period and the estimation of the baseline model (developed above) at each stage. The test starts at some minimal sample length—minimal time t—which allows for the estimation of the benchmark model, and then recursion proceeds with the addition of cross-sectional vectors until the model is estimated using the full sample.

At each stage in estimation, one-step-ahead prediction errors, called recursive residuals, are calculated as (see the Appendix for details):

$$W_t = y_t - X_{ta} b_{t-1} \qquad \text{(A1.1)}$$

where y_t is a vector of N cross-sectional observations at time t, b_{t-1} is the vector of coefficients calculated using the complete sample from time 1 to $t-1$ (i.e. last period's information), X_{ta} is the matrix of all observations on N cross-sectional units in period t, and W_t is the calculated vector (of dimension N equal to the number of cross-sectional units) of recursive residuals.

Next, in each period t, elements of vector W_t are averaged using a complex function, which generates a scalar value W_j* for each period. These values W_j* together, comprise a series called the standardized weighted averages of prediction errors, which goes from the beginning of recursion period to the end of the sample. This series is subsequently used in the calculation of the panel version of the CUSUM test statistic:

$$W_t ** = \frac{1}{s}\sum_{j=\min}^{t} W_j * \quad t = min, \ldots, T \qquad \text{(A1.2)}$$

where s is the standard error of regression calculated using the full sample, and *min* is the minimal period needed (in terms of degrees of freedom) to estimate all parameters in the model. Hence, CUSUM, as the name implies, is the cumulative sum of the standardized weighted averages of prediction errors.

The sequence $W_{min}**$, $W_{min+1}**$, …, W_t** is a sequence of approximately normal random variables with the same general statistical properties as in Brown, Durbin, and Evans (1975). Specifically, $E(W_t**) = 0$, and $V(W_t**)$ and $C(W_t**, W_s**)$ are known functions of time and the number of parameters (see BDE for details). This implies that W_t** can be approximated by a continuous Gaussian process, and, therefore, we may place a pair of lines symmetrically above and below the zero line such that the probability that the CUSUM plot W_t** will cross either line at a desired level of significance.

The null hypothesis is no structural change, which is implied by $E(W_t**) = 0$. A crossing of the lines as described above testifies to a statistically significant violation of the null hypothesis of no structural change ($E(W_t**) = 0$), since the CUSUM of (weighted averaged and standardized) recursive prediction residuals (i.e. one-step-ahead prediction errors) diverge from their expectations in the post-change period. The direction of the change (positive or negative) can be inferred from whether the negative or positive significance band is crossed. By using such graphs of CUSUM against time, and placing these critical value lines under H_0, it is possible to test for changes in model structure at various significance levels (Maskus 1983).

In addition to CUSUMS, we graph these recursive residuals (forecast errors) without summing them, along with +- 2 standard errors bands (Figure 3). This helps pinpoint specific dates when prediction residuals were significantly different from zero (Dinardo and Johnston 1996); these confirm the story told by CUSUMs.

Mathematical Details

This very closely follows Maskus (1983). Consider the question of testing for time-related structural change in the parameters of a pooled cross-section and time- series model:

$$Y_{it} = X'_{it}\beta + E_{it} \quad i = 1, 2, \ldots, N, t = 1, 2, \ldots, T \qquad \text{(A2. 1)}$$

where at time t and for cross-sectional unit i, Y_{it} is the observation on the dependent variable and X'_{it} is the column vector of observations on K regressors. It is assumed that the regressors are independent of the error terms, that the error terms are normally and independently distributed with means zero and common variance σ^2, and that it is permissible to examine the parameters for variation only over time, rather than both over time and among cross-sectional units. Thus, the testable hypotheses are

$$H_0\text{: } \beta_1 = \beta_2 = \text{---} = \beta_T = \beta \qquad \text{(A2. 2)}$$

$$H_A\text{: not } H_0$$

The CUSUM procedure mentioned above may be modified for pooled cross-section and time-series data in the following way. Let the forecasts of the regression coefficients be annually updated by simultaneously adding all N observations from the successive cross-sections. The result is a vector of N recursive residuals at each step and we wish to specify meaningful summary statistics which incorporate information from all of them. If it is assumed that time-related structural changes tend uniformly to be experienced across the cross-sectional units, then this residual vector will diverge from the zero vector in any post-change period.

Formally, let X_{ta} denote the matrix of regressor observations from period t on the N cross-sections, let y_t denote the vector of observations on the dependent variable and let E_t be the vector of disturbance terms. Then successively stack the observations over t years, beginning with the first year of analysis, so that, in general,

$$Y_t = X_t \beta + V_t \qquad \text{(A2. 3)}$$

where

$$Y_t = (y_1 , y_2, \ldots, y_t)', \quad V_t = (E_1, E_2, \ldots, E_t)'$$

and

$$X_t = \begin{bmatrix} X_{1a} \\ X_{2a} \\ \vdots \\ X_{ta} \end{bmatrix}, \qquad t = 1,2,\ldots,T$$

Let $b_t = (X_t'X_t)^{-1} X_t'Y_t$ be the OLS estimator of β in year t. Consider then the forecast error vector:

$$W_t = y_t - X_{ta} b_{t-1} \qquad \text{(A2. 4)}$$

which has dimension (N x 1). Under the null hypothesis of no change in β and given the assumptions listed earlier, we see that

$$E(W_t) = 0$$

and

$$V(W_t) = \sigma^2\{X_{ta} (X'_{t-1} X_{t-1})^{-1} X'_{ta} + I) = \sigma^2\Omega_t \qquad \text{(A2. 5)}$$

Further, by the normality of the error vector, we may say that

$$W_t \sim N(0, \sigma^2\Omega_t) \qquad \text{(A2. 6)}$$

Next, we may compute what shall be called the "standardized mean forecast residual"

$$W_t^* = \delta' W_t / \sqrt{\delta'\Omega_t \delta} \qquad \text{(A2. 7)}$$

where δ is an (N x 1) vector of parameters which serve to weight the cross-section residuals, and recognize that

$$E(W_t^*) = 0$$

$$V(W_t^*) = \sigma^2 \qquad \text{(A2. 8)}$$

Further, the standardized mean forecast residuals are mutually independent. Thus, the modified CUSUM statistic (equations (5) in the main text) has the stated properties.

Statistical Summary of Variables

Note: since the time period differs between property type (except for office and industrial), the moments for national variables and the number of included observations differ as a result.

Office

Variable	Obs	Mean	Std Error	Minimum	Maximum
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

Variable	Obs	Mean	Std Error	Minimum	Maximum
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

Variable	Obs	Mean	Std Error	Minimum	Maximum
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

Variable	Obs	Mean	Std Error	Minimum	Maximum
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

MSA's 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
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**

Figure 1
CUSUM Plots: 10% Significance Bands
Iteration starting in 1987q1 (1988q1 for multifamily)

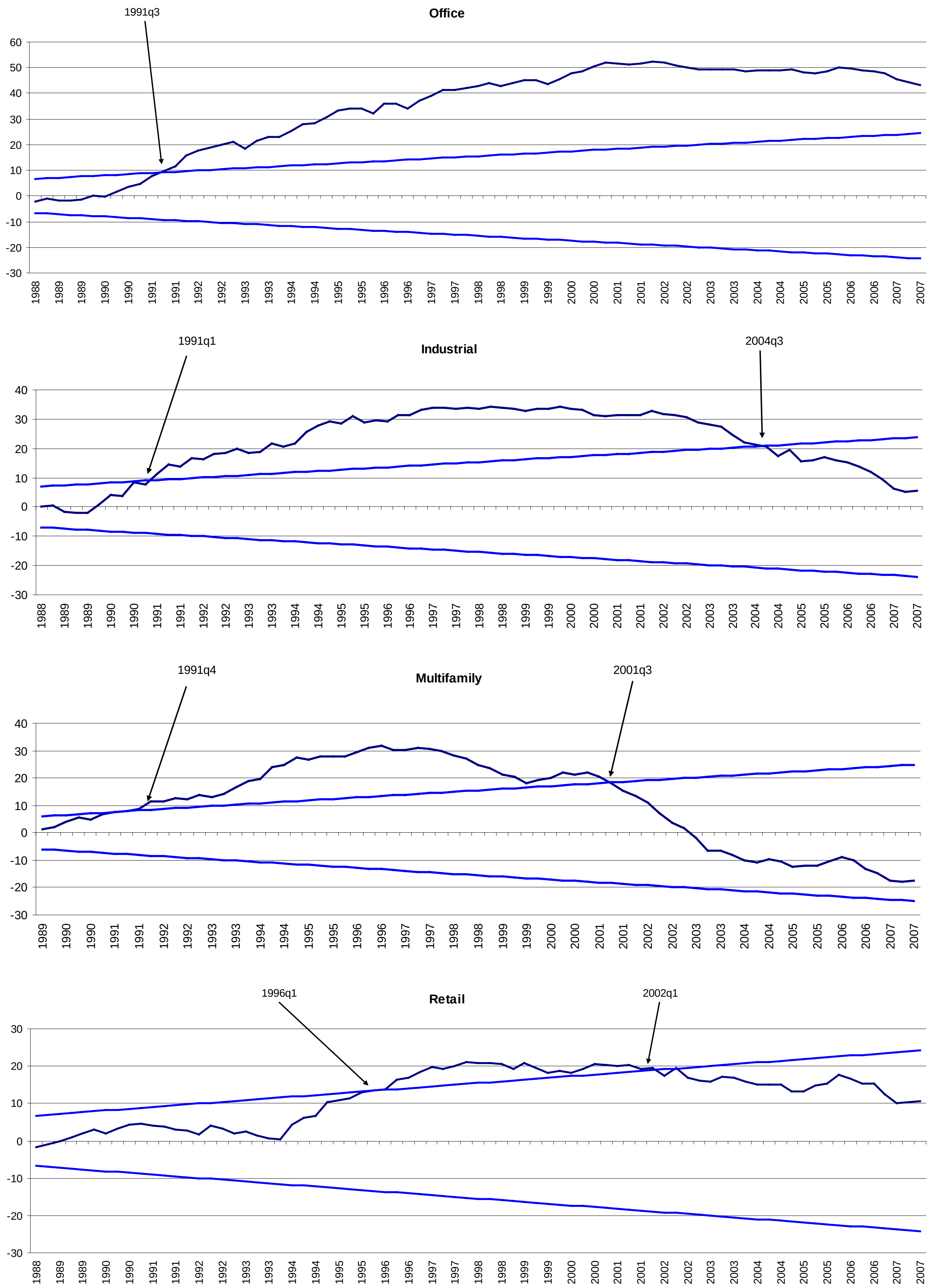


Figure 2
Recursive Coefficient Tests for Structural Change:
Recursive Coefficients Change and +- 2 Standard Error Bands

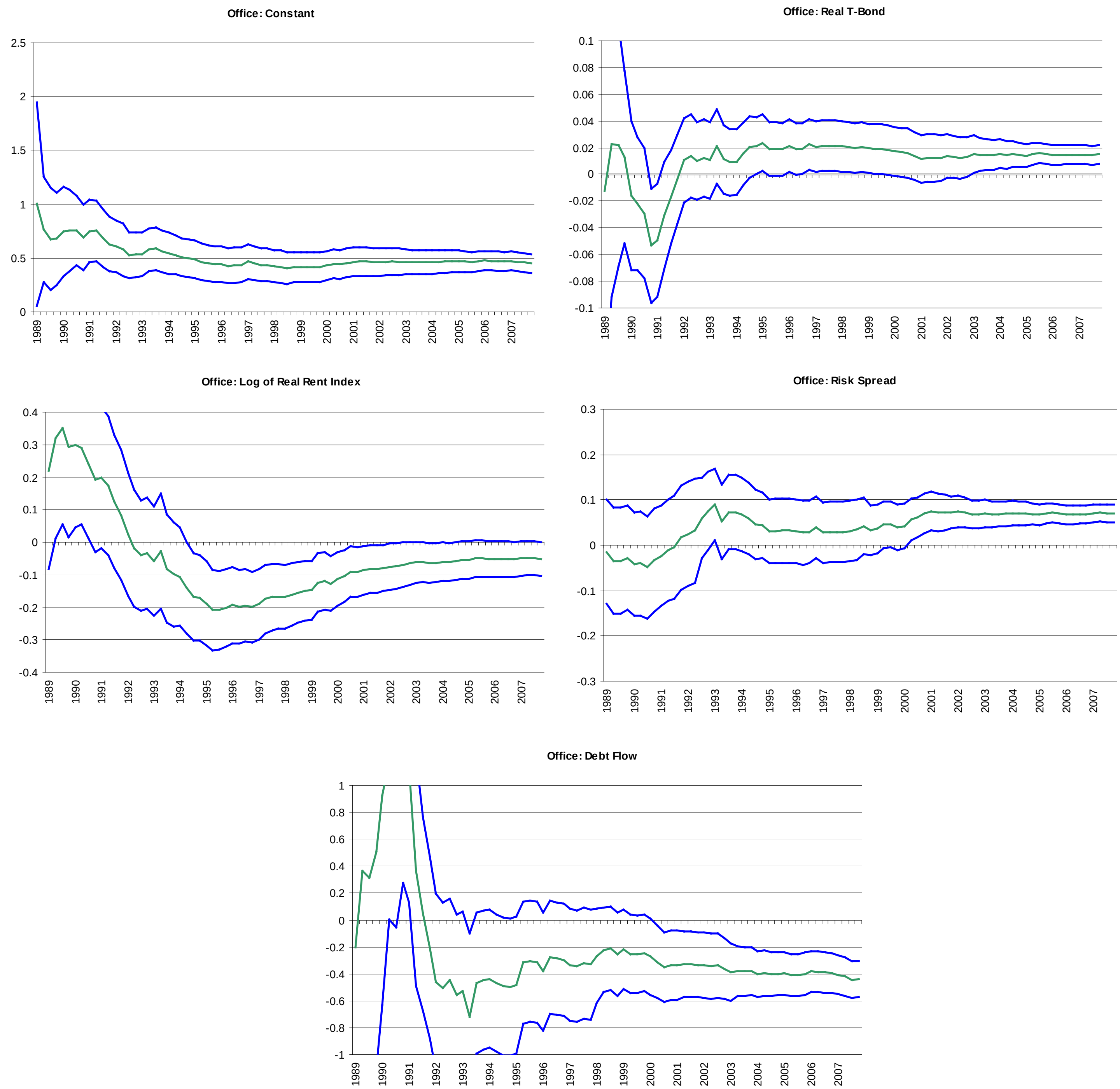


Figure 2
Recursive Coefficient Tests for Structural Change:
Recursive Coefficients Change and +- 2 Standard Error Bands

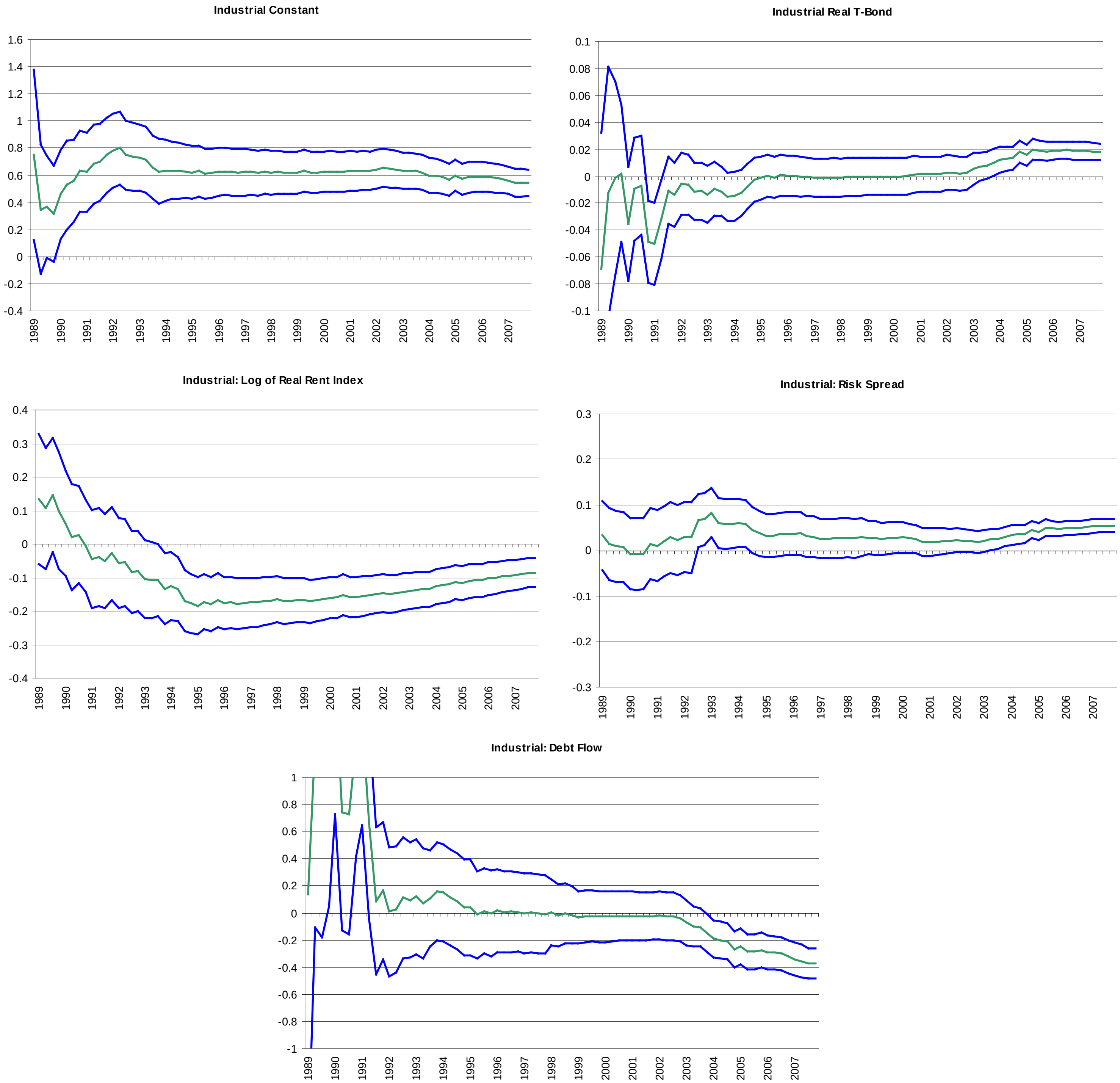


Figure 2
Recursive Coefficient Tests for Structural Change:
Recursive Coefficients Change and +- 2 Standard Error Bands

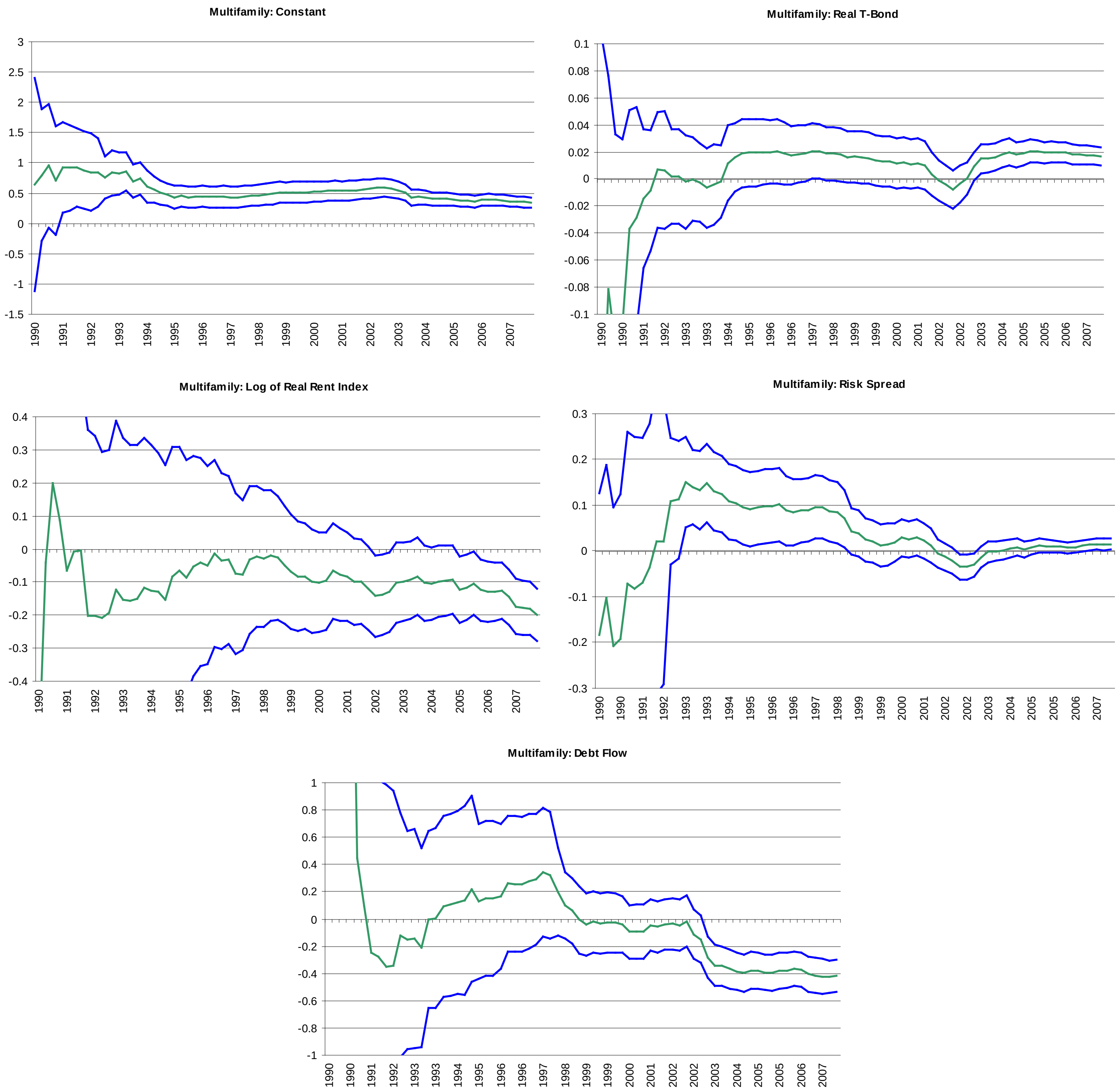


Figure 2
Recursive Coefficient Tests for Structural Change:
Recursive Coefficients Change and +- 2 Standard Error Bands

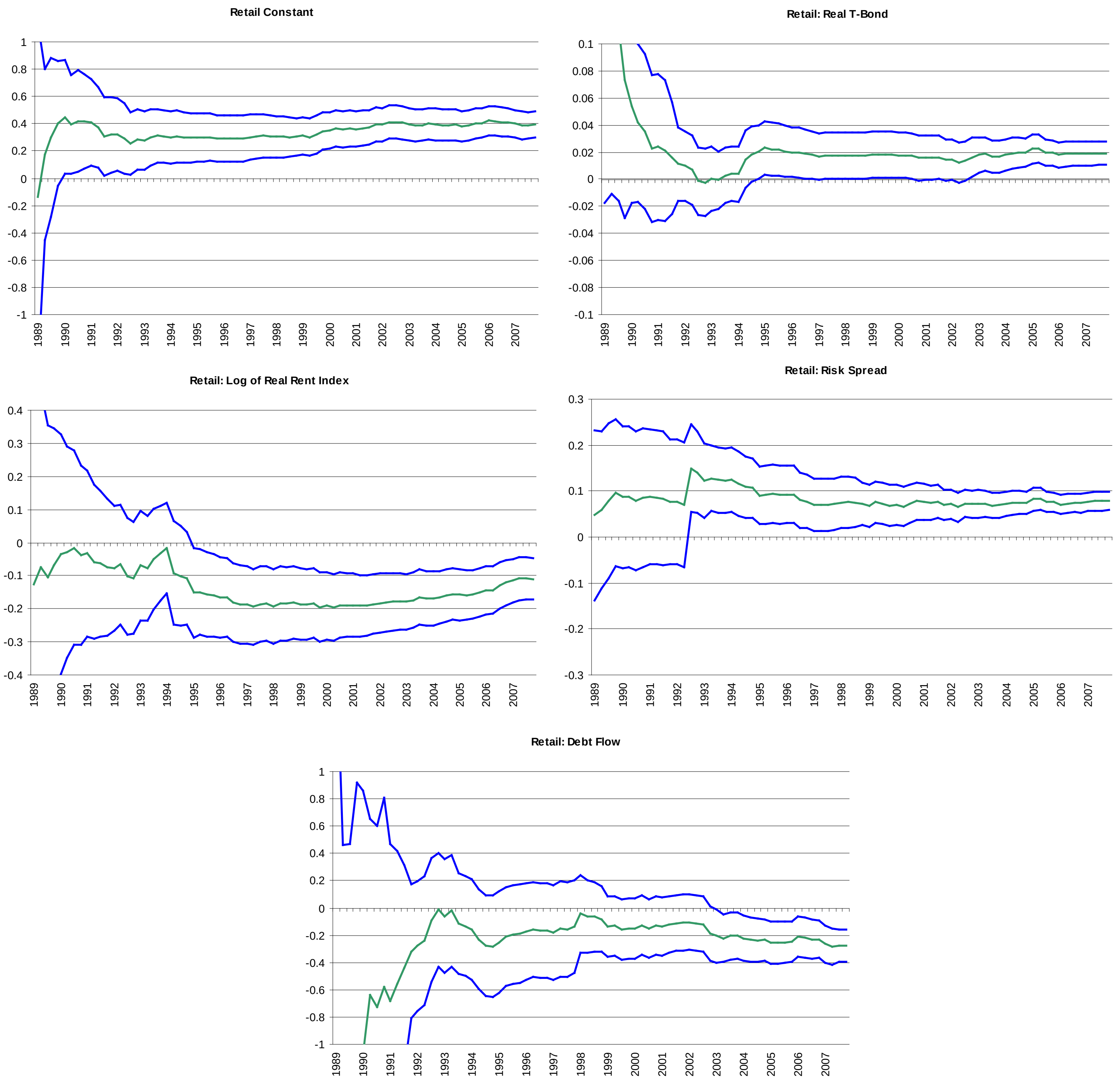
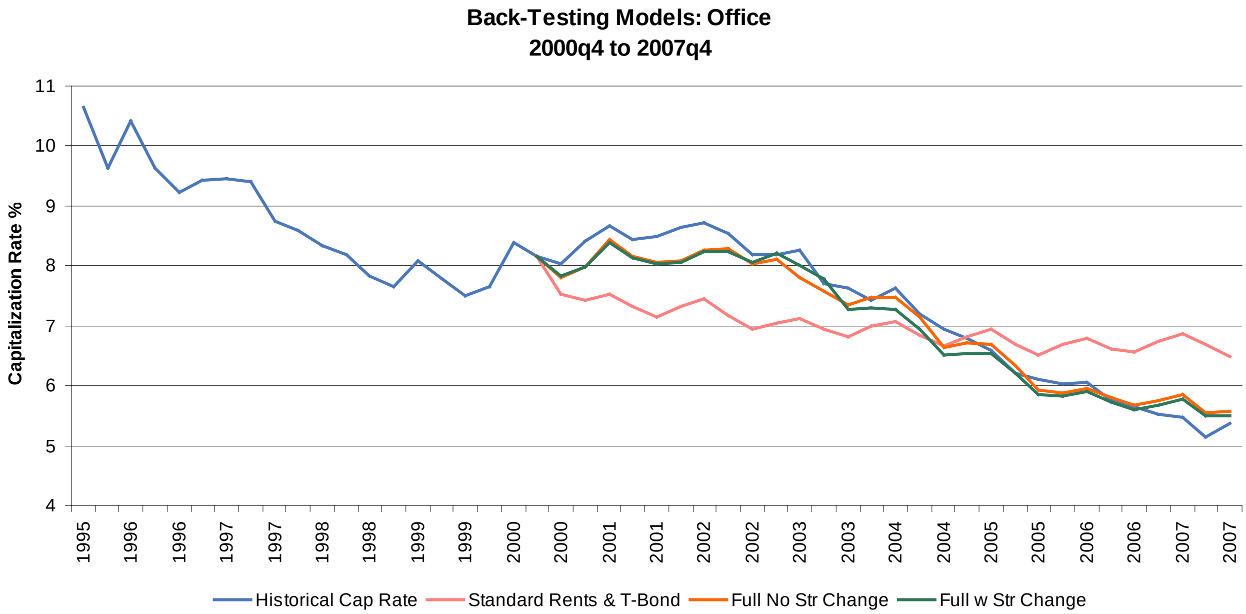


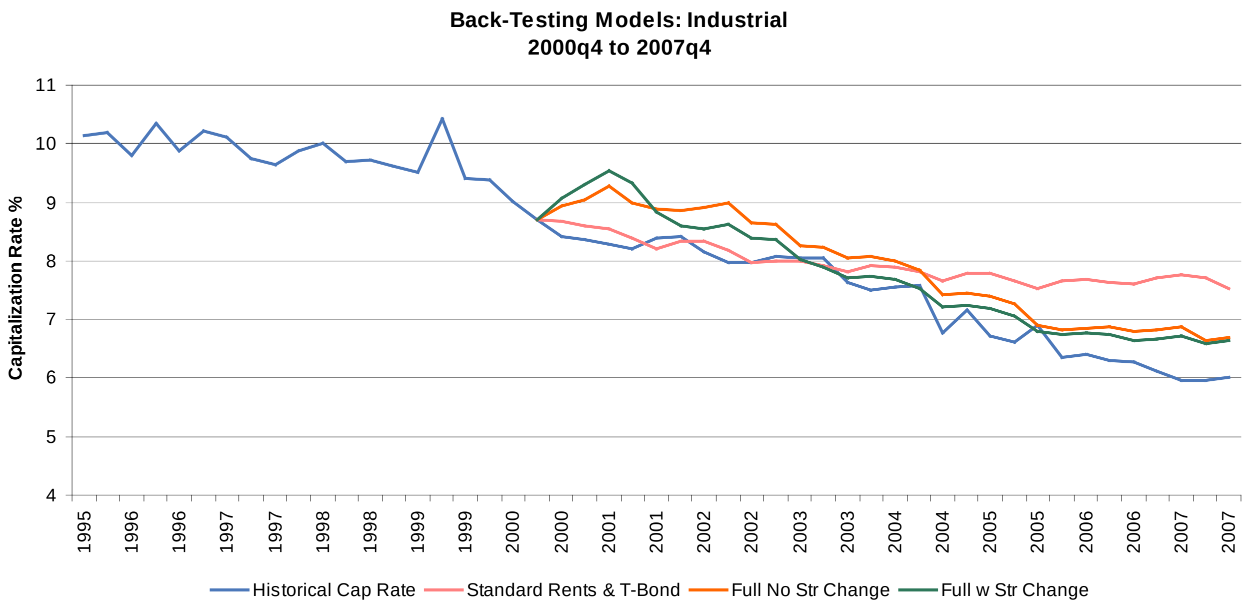
Figure 3
Back-Testing Model Specifications



Back-Test 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 2000q4 through 2007q4

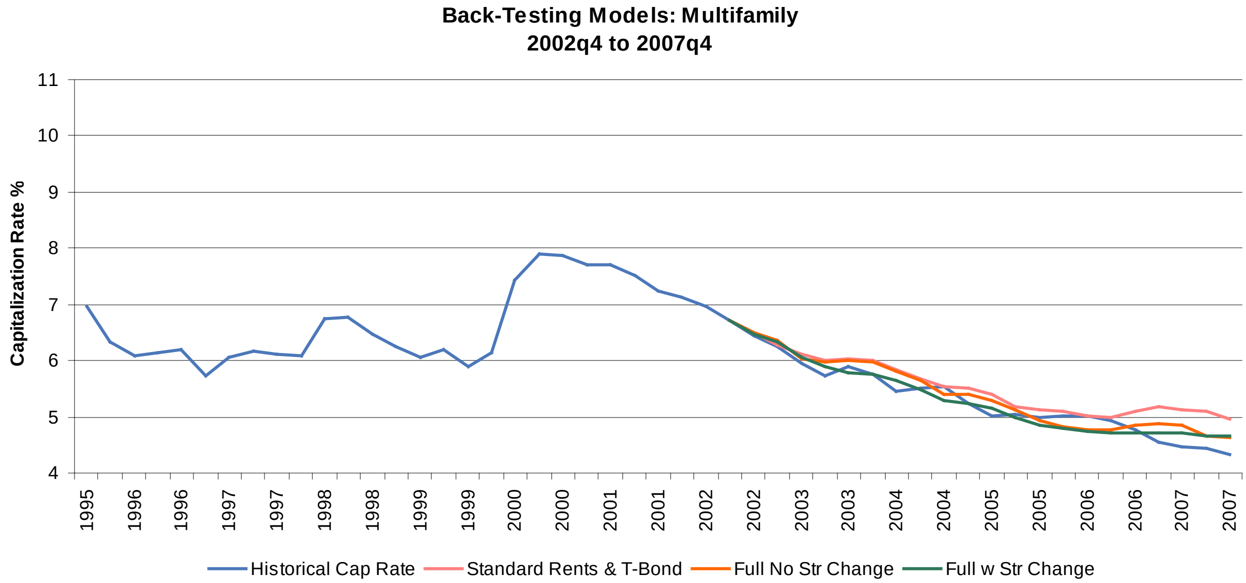


Back-Test Forecasting Performance: Industrial

Model	Mean Error of Forecast	Mean Absolute Error of Forecast	Theil U
Standard Rents and T-Bond	-1.5101044	1.5101044	0.5611
Extended no Structural Change	-0.6815805	0.6815805	0.2532
Extended with Structural Change	-0.6245786	0.6245786	0.2321

Based on 29 forecast steps from 2000q4 through 2007q4

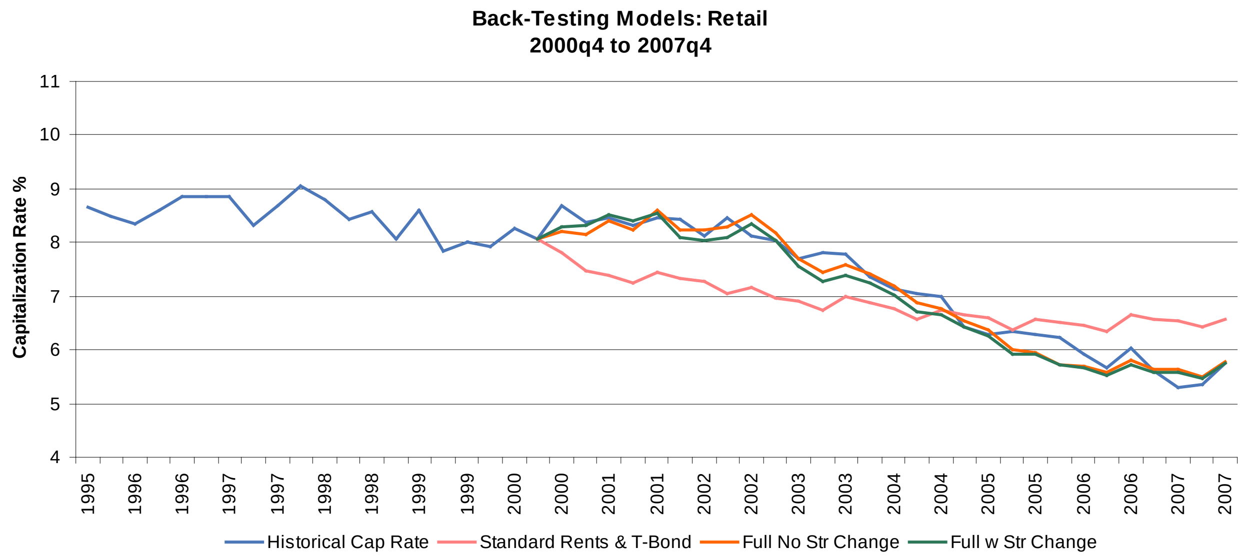
Figure 3
Back-Testing Model Specifications



Back-Test 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 2002q4 through 2007q3



Back-Test 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 2000q4 through 2007q4

Table 1
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 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

Table 2
Multiple Regression Results
Standard Literature-based Specification with Rents, T-Bond, 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)
$Log(Real\ Rent\ Index)_t$	-0.038 (-1.810)	-0.047 (-2.315)	-0.158 (-3.708)	-0.134 (-3.800)
Real T-Bond 10year	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 is quarterly from 1980q1 through 2007q4

Table 3
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)
$Log(Real Rent Index)_{t-s}$	-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 10year	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 is quarterly from 1980q1 through 2007q4				

Table 4
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)
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 10year	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 pooled OLS specification: time series and cross-sectional observations pooled together and estimated via OLS with heteroskedasticity corrected errors All data is quarterly from 1980q1 through 2007q4

Table 5
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 10year	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 is quarterly from 1980q1 through 2007q4

Table 6
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 yearq, 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 yearq = 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**