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What Moves Retail Property Returns at the Metropolitan Level?

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Abstract: *In this article the determinants of metropolitan-level appraisal-based retail property returns are examined by estimating a six-equation model of retail construction starts, retail sales, stock-market returns, commercial mortgage rates, inflation, and the logarithm of stock-market volatility. Residuals from these equations are then used to explain actual movements in retail real estate returns. Our empirical procedure looks at both unadjusted and unsmoothed appraisal-based retail real estate returns. The general finding is that unsmoothed appraisal-based retail real estate returns lag significantly behind market conditions. Furthermore, the results suggest that very little of the variation in metropolitan-level appraisal-based retail real estate returns can be explained by macroeconomic news events.*

This article uses metropolitan-level data on property returns to study the determinants of retail property return movements. The source of the retail property return data is the NCREIF (National Council of Real Estate Investment Fiduciaries) Index. We know that retail property returns ought to reflect the fundamentals of the retail leasing market (particularly since retail leases often have provisions for base rent and additional rent based on retail sales), but we do not know how quickly retail property returns change as expectations in the market place change. In this study, we provide new insights into how quickly real estate returns respond to various types of economic news by estimating a model of retail real estate price movements along the lines of Cutler, Poterba, and Summers (1989).

There are six main estimated relationships in the model–a retail construction starts equation, a reduced-form treatment of the logarithm of retail sales, and a vector autoregressive (VAR) model of stock-market returns, the interest rate on commercial mortgages, the inflation rate, and the logarithm of stock-market volatility. All equations are estimated using quarterly data, beginning with the earliest period allowed by the data for each equation and ending in 1994:2. Each model has been kept small–particularly in the treatment of the stock-market returns, the interest rate on commercial mortgages, the inflation rate, and the logarithm of stock-market volatility–so that it would be manageable and readily estimated.

Retail construction starts are determined by an aggregate retail gap formula. Here, demand factors like the expected change in retail sales are assumed to influence retail starts through stock-level forces. Following the work of Muth on stock-adjustment models, the retail starts equation also includes a proxy for the part of production that is expected to replace depreciated, removed, or converted retail space. The model is estimated separately for each metropolitan area.

The reduced-form equation for the logarithm of retail sales is specified in a format consistent with the recent work of Wheaton and Torto (1995). The equation assumes that the logarithm of retail sales moves toward its equilibrium value, but only gradually. The equation also assumes that retail sales are directly tied to household income in the metropolitan area. Demographic variables are included in the model to reflect the shift in the distribution of the population toward those age categories that tend to have below-average propensities to spend. Once again the model is estimated separately for each metropolitan area.

We adopt a less structured approach to the treatment of the stock-market returns, the interest rate on commercial mortgages, the inflation rate, and the logarithm of stock-market volatility. The model estimated relates each macroeconomic variable to its own history and that of the other variables. This formulation avoids having to classify the underlying variables into endogenous and exogenous variables.

Next, simulations of the model are performed to obtain the residuals across each of these equations. We then treat the residuals from these equations as macroeconomic news and market innovations and use them as explanatory variables for appraisal-based retail real estate returns. The R^2 for this equation measures the importance of these types of macroeconomic news and market innovations in explaining appraisal-based property returns. We estimate this model using appraisal-based returns on neighborhood and community shopping centers. We also estimate the model with and without Fisher, GeItner, and Webb's (1994) correction for appraisal smoothing bias.

Our findings suggest that only about 3% of the variance in unsmoothed appraisal-based retail real estate returns can be explained by contemporaneous macroeconomic news and market innovations. These findings run contrary to those obtained for common stocks. Roll, in his 1988 presidential address to the American Finance Association, for example, suggests that slightly less than 40% of the variance of stock price changes can be explained by contemporaneous news events. Fama (1990), on the other hand, finds that almost two-thirds of the variance of aggregate stock price movements can be accounted for by variables proxying for corporate cash flows and investors' discount rates. Fama uses leads of some variables as well as contemporaneous values as an informal way to allow for extra information that market participants may have about future macroeconomic developments.

Our analysis further suggests that regressions with lagged macroeconomic news events and market innovations (lags of up to three years) are able to explain 28% of the variance in unsmoothed appraisal-based retail property returns. These lags point out that substantial time is needed before news in the space market causes property returns at the metropolitan-level to change (which is an important finding in a world in which metropolitan-level real returns are used to make real estate investment and portfolio decisions). The sort of evidence presented here also suggests that very little of the variation in the unsmoothed appraisal-based retail property returns is explained by macroeconomic news events.

On the basis of the evidence presented here, we can also identify which retail markets appear to be more predictable than others. Usually in the study of real estate returns, we abstract from issues regarding the location of the market. It is interesting to reflect, however, that significant differences in yields among metropolitan areas and by property types persisted through almost the entire 1980s. We find that these differences are highly correlated with our ability to explain the variation in retail property returns. Generally, where returns are high, our explanatory ability is below average. Likewise, where returns are low, our explanatory ability appears to be above average. We also find that some metropolitan areas are more predictable and potentially more informationally inefficient (which we measure by noting whether past values have an effect on current values) than other metropolitan areas.

The article proceeds as follows. We first review the conventional wisdom concerning real estate performance and appraisal-based returns. We next outline our theoretical framework and provide a set of estimated equations. We then present our regressions of retail real estate returns on our economic news variables. Our final section contains some concluding remarks.

1. Theoretical Background

Before proceeding it is important to place our analysis in context in both the real estate and finance literature. Of the existing published literature in finance, a number of analyses examine the determinants of stock-market returns (see, among others, Campbell, 1987, 1991; Campbell and Shiller, 1988; Cutler, Poterba, and Summers, 1989; Fama and French, 1989; McQueen and Thorley, 1991; Poterba and Summers, 1988; and Roll, 1988). These studies generally find that stock-market returns move in a systematic, as opposed to a random, manner.

Of the existing published literature in real estate, several recent papers provide evidence on the determinants of real estate stock returns. For example, Mei and Liu (1994) and Mei and Saunders (1995), using an approach similar to Campbell (1987) and Ferson (1989), attempt to predict real estate stock returns using a simple accounting relationship of the behavior of long-term real estate returns. The findings generally suggest that there is an inverse relationship between ex post and ex ante returns; which is to say, large excess real estate stock returns today tend to be associated with smaller ex ante real estate stock returns in the future, and vice versa. Other work has examined the predictable components of appraisal-based real estate returns. These studies generally suggest that most of the change in property value over time results from changes in return expectations or requirements.

Related to this work, Fisher (1992) and DiPasquale and Wheaton (1992) establish a general equilibrium framework of real estate markets within which we may view the relationships between the real estate space and asset markets. Although informally presented, they explain how exogenous shocks in both the capital markets and the market for space can result in new construction and adjustments in rents and asset prices as well as in the stock of real estate.

The essence of these models is contained in the formal treatment by Geltner and Mei (1995). Working from the identity defining the asset return $r_{t+1} \equiv \log(P_{t+1} + D_{t+1}/P_t)$, Geltner and Mei obtain a first-order Taylor expansion

$$r_{t+1} \approx k + \rho \log P_{t+1} + (1-\rho)\log D_{t+1} - \log P_t, \tag{1}$$

where the parameter ρ is the average ratio of the asset price to the sum of the asset price and the cash flow (a number slightly less than one), and the constant k is a nonlinear function of ρ. This equation can be rewritten as an expectational difference equation relating log P_t to log P_{t+1} log D_{t+1} , and log r_{t+1}. Imposing the terminal condition $\lim_{t\to\infty} E_t[\rho^i \log P_{t+1}] = 0$ to prevent explosive rational bubbles allows (1) to be solved forward:

$$\log P_t = \frac{k}{1-\rho} + (1-\rho)\sum_{j=0}^{\infty} \rho^i E_t[\log D_{t+1+j}] - \sum_{j=0}^{\infty} \rho^i E_t[r_{t+1+j}]. \tag{2}$$

Equation (2) says that the observed asset price is equal to a constant plus the expected discounted value of all future cash flows D_{t+1+j} less future returns r_{t+1+j}. The cash flows reflect expectations in the space market and the returns reflect expectations in the capital markets. Geltner and Mei show how both expected future cash flows and returns are determined by movements in a set of economic state variables and their interrelationship. We extend Geltner and Mei's analysis by explicitly relating retail property returns (adjusted and unadjusted for appraisal smoothing) to unexpected changes in retail construction starts, retail sales, stock-market returns, commercial mortgage interest rates, the inflation rate, and stock-market volatility.

We would stress that we are not out to maximise R^2 in explaining the movements in retail property returns. If we wanted to do that, we would regress current retail property returns on lagged returns. Moreover, we are not interested in testing whether retail property returns are determined by putting weight on unexpected good news or bad news about future net earnings, or unexpected good news or bad news about future yields, with no other data beyond retail real estate returns entering the analysis.[1]

The logic that unexpected changes in retail sales should cause retail property returns to change is straightforward. Retail leases (at least in the United States) often have provisions for base rent and additional rent based on retail sales. Thus, insofar as the landlord's income is directly related to the success of the tenant's operations, movements in retail property returns should closely follow unexpected changes in real retail sales.

We turn now to a discussion of the relationship between unexpected changes in retail construction activity and retail property returns. Suppose we start by assuming (as many would say) that the supply of retail space is inelastic. Then with a positive supply change, rent levels should fall, which will generate lower asset prices and lower overall retail property returns. And so this has the result that an unexpected increase in retail construction activity should cause retail property returns to fall (see, for example, DiPasquale and Wheaton, 1992). We could, of course, equally well have assumed that the supply of retail space (at least in the long-run) is elastic. This situation is mentioned because with an elastic supply curve, an unexpected increase in retail construction activity should leave rent levels and asset prices unaffected (which means that retail property returns would also be unaffected); and, finally, some retail properties may be protected from falling rents by a natural monopoly (which again means that it is perfectly possible for there to be a rather weak link between unexpected changes in retail construction activity and retail property returns).[2]

2. Stock-Level Demand for Retail Space

2.1. Modeling

Several recent papers have examined the stock-level demand for retail real estate (see, for example, Benjamin, Jud, and Winkler, 1994; Eppli and Shilling, 1995). Our specification of the equation for retail real estate construction emphasizes flow-level, demand-side factors. Specifically, two factors enter our model of retail real estate construction.

2.1.1. Projected Retail Gap

Projected retail gap should be the primary force determining retail real estate construction. A particularly convenient specification of the projected retail gap within a metropolitan area is

$$K = \beta_0 + \beta_1 \Delta S^e + \varepsilon, \tag{3}$$

where K is the projected retail gap, ΔS^e is expected change in total retail expenditures (measured in real dollars), and β_1 is one over average sales per square foot.

This model assumes that developers should build when the projected real demand in square feet $K > 0$; the developer should not build when the projected real demand in square feet $K \leq 0$. Since it takes two to three years to bring a retail shopping center on the market, the developer is principally concerned with future retail gaps rather than the present one.

2.1.2. Expected Removals

Expected removals enter the equation as a measure of the part of production that replaces depreciated or removed shopping centers. The specification assumes that such replacement demand can be forecasted based on some knowledge of current trends and past removal patterns.

Combining these two factors into one equation, our model of retail real estate construction is

$$ST = \beta_0 + \beta_1 \Delta S^e + \beta_2 REM^e + \varepsilon, \tag{4}$$

where ST is starts of retail shopping centers (measured in square feet), and REM^e is expected removals.

To estimate (4), we assume expectations of ΔS are based on distributed lags on past values of $\Delta S.$ We make a similar assumption for expectations regarding $REM.$ Thus, the model we estimate is given by

$$ST = \beta_0 + \beta_1(w_0\Delta S_{-1} + w_1\, \Delta S_{-2} + \cdots + w_k\, \Delta S_{-k}) \\ +\beta_2(v_0 REM_{-1} + v_1 REM_{-2} + \cdots + v_n REM_{-n-1}) + \varepsilon, \quad (5)$$

where

$$w_i = c_0 + c_1 i + c_2 i^2 \text{ for } i = 0,1,\ldots,k \quad (6)$$

and

$$v_i = d_0 + d_1 i + d_2 i^2 \text{ for } i = 0, 1, \ldots, n. \quad (7)$$

Substituting (5), (6), and (7), into (4) and rewriting the original specification, we get

$$ST = \beta_0 + b_1\Delta S_{-1} + b_2\Delta S_{-2} + \cdots + b_k\Delta S_{-k} \\ +\gamma_1 REM_{-1} + \gamma_2 REM_{-2} + \cdots + \gamma_n REM_{-n-1} + \varepsilon, \quad (8)$$

where the lag weights can be estimated using a polynomial distributed lag model.

For the analysis, data on quarterly retail construction starts and removals come from F. W. Dodge. The retail expenditures are available quarterly from the Department of Commerce. All three series were obtained from Data Resource Inc. (DRI). Nominal sales data are converted into real sales by deflating by the consumer price index, all items. These data are reported on the MSA level for most large metropolitan areas; however, retail sales are reported for a limited number of markets, thus limiting our analysis to eleven MSAs.

Table 1 presents summary characteristics of the data. This table is our attempt to present compactly the salient facts from each of the eleven metropolitan areas in our study. The facts are these: Average annual shopping center construction starts, shown in column 1, vary from a low of 360,000 square feet per year for the Milwaukee MSA to a high of 3,160,000 square feet for the Chicago MSA. Removals, shown in column 2, vary from a low of 192,000 square feet per year for the Milwaukee MSA to a high of 1,436,000 square feet per year for the Chicago MSA. Strikingly, Atlanta, Houston, San Diego, and Tampa all show above average year-to-year growth rates in their stock of retail space (see column 3). Milwaukee and St. Louis, on the other hand, show the smallest year-over-year growth in the stock of retail space. These growth patterns conform very well to expectations. There are five metropolitan areas that experienced large real growth rates of shopping center sales–Atlanta, Detroit, St. Louis, Oakland, and Tampa (see column 4). Atlanta and Tampa, for example, had real growth rates in excess of 5% per annum. Interestingly enough, Atlanta and Tampa also experienced relatively high rates of population growth.[3] For reasons that we attempt to explain in section 4, five markets experienced declining sales per square foot of shopping center space–Chicago, Houston, Los Angeles, Milwaukee, and San Diego (see column 5).

2.2. Empirical Results

We begin our study by inspecting the relationship between shopping center construction starts and changes in retail sales, by metropolitan area, over time. As the data show (not reported here because of space constraints), it is quite apparent that shopping center construction starts and changes in retail sales move in virtual lockstep (with a possible lag). With this encouragement, we proceed to a formal test of the model by estimating (8) using a second-degree polynomial (with no endpoint restrictions). The length of lag is extended as long as the expected positive relationship held.

Results of our estimations are presented in table 2, with t-statistics reported in parentheses.[4] In all cases, the structure of the underlying model seems to fit the data reasonably well. The R^2s range from a low of 0.19 for St. Louis (which is a difficult market for us to explain owing to its high retail sales growth and its low growth in the stock of retail space) to a high of 0.77 for Atlanta.[5]

The lag weights implied by the mean coefficients in table 2 are given in table 3, by metropolitan area. With one or two exceptions, Houston and San Diego, there would appear to be strong evidence of a positive and significant relationship between shopping center construction starts and lagged values of changes in retail sales (even though these lag weights do not follow a perfectly convex relationship as expected). Both the humped weight pattern and the nearly three-year period for complete adjustment are generally consistent with our expectations. Moreover, the results generally suggest that the first several lag weights are insignificant. The results also generally suggest that the lag weights in the interval between two to seven quarters are positive and significant at the 10% level. The poor results for Houston and San Diego may be partially explained by the significant overbuilding that took place in both of these markets over the sample period.

Lastly, there is strong evidence of a positive relationship between shopping center construction starts and lagged values of removals. For reason of space, however, these results are not reproduced here.

2.3. Forecast Errors

We report here forecast errors (actual minus predicted sales) associated with (6) for the period 1978:1 to 1988:4. These forecast errors are estimated by ex post simulation analysis. The analysis is as follows: Ex post or historical simulations of the models begin in the first quarter of 1978 and run forward until the fourth quarter of 1988. Historical values in each quarter are used for the exogenous variable. We report in this section only the average forecast errors (in percent per annum) over the 1978:1 to 1988:4 time period because of the pace of commercial property construction and the extent of the overbuilding that took place nationwide during this time period.[6] The conclusions are these: Owing in large part to the clustering of the residuals in (6), the forecasting errors for our model are quite large. Houston and Milwaukee, for example, have average forecasting errors over the 1978:1 to 1988:4 time period in excess of -150%. There are two metropolitan areas, Atlanta and Detroit, with large positive forecast errors and large annual growth rates in construction starts (in excess of 15%). The remaining MSAs in our sample have negative forecast errors and slightly lower annual growth rates in construction starts.

3. Retail Sales

3.1. The Wheaton-Torto Sales Forecasting Model

We require a precise estimate of projected retail sales in order to use the residual from such a projection as an explanatory variable for our appraisal-based retail real estate returns. Wheaton and Torto (1995) provide a starting point for the specification of the sales equation. To find out how retail sales are related to income, Wheaton and Torto use a reduced-form estimation–that is, they neither try to find an underlying utility function nor model the details of the decision-making process. Estimates are made for each of seven retail industry categories characterizing "store" sales, excluding automotive and catalog sales and fuel dealers, obtained by SIC code in nominal dollars. In addition to personal income in nominal dollars, the specification also included lagged sales to allow for the gradual adjustment of sales to movements in income.

While Wheaton and Torto's equation performed well from an adjusted R^2 standpoint (0.97), most of the explanatory power of the equation was bound up in the lagged sales variables, and the significance of the income coefficients was primarily due to metropolitan area population growth. We thus additionally explored an alternative specification.

3.2. An Alternative Specification

There is a large literature in the marketing and operations research that concentrates on empirical comparisons among alternative sales forecasting techniques.[7] However, these efforts are intended primarily to evaluate performance with respect to predictive error without regard to theory. We attempt here to specify a reduced form sales equation based on a more formal notion of underlying economic principles that compares favorably in performance to these models yet extends the Wheaton-Torto specification.

For our analysis, total retail expenditures are specified

$$\log S \ = \ \alpha_0 + \alpha_1 \log Y \ + \ \alpha_2 \log HH + \alpha_3 \log D + \alpha_4 \log(P_R/P) + \alpha_5 \log\left(\frac{P_P}{P}\right) + \alpha_6 \log S_{-1} + \varepsilon, \qquad (9)$$

where S is total retail expenditures (measured in real dollars) for the metropolitan area, Y is average household income (measured in real dollars), HH is number of households, D is a vector of demographic shift variables, P_R/P is relative retail price index, and P_P/P is relative producer price index.

Each of the first three variables reflects a component of the demand for retail goods. The first is average household income, which (as is borne out) significantly affects retail expenditures. The second is a proxy for market size. We expect–and at least want to test for–a positive and significant impact of market size on total retail expenditures. We also want to test average household income and number of households to determine which variable has a more significant effect on total retail expenditures. The third is a vector of demographic shift variables. We categorize the population in each metropolitan area into groups. Our groupings include population in the thirty-five to fifty-four age bracket and population in the sixty-five and older age group. We also include a measure of unemployment in each metropolitan area.

Each of the next two variables reflects relative prices. The relative retail price introduces an ambiguous element into the model. From a demand standpoint, quantity demanded should fall as P_R/P rises. However, from a supply standpoint total expenditures may rise or fall with an increase P_R/P depending on the relative magnitudes of the changes in price and quantity. Obviously, in price ranges where demand is inelastic, we would expect total expenditures to increase as P_R/P increases. Likewise, in price ranges where demand is elastic, we would expect total expenditures to fall as P_R/P increases. The relative producer price index measures the general price level of goods at their first level of transaction. A higher producer price index, as a consequence, should lead to higher retail prices and, depending on the overall price elasticity of demand, higher or lower retail expenditures.

The last variable in (9) allows us to model changes in retail expenditures as a partial adjustment process. More specifically, it is assumed that total retail expenditures in a metropolitan area will move toward its equilibrium value, but only gradually at a speed depending on one minus α_6.

The data used herein come from two sources. First, the quarterly data regarding retail expenditures and prices come from the Department of Commerce. The three price indices are the consumer price index, the retail component of the consumer price index, and the producer price index. For estimation, we constructed two relative price indices. The second data source is the U.S. Census for average household income, number of households, and population. All variables (except for the producer price index) are metropolitan-level specific. Also, all data (except for the three price indices) were obtained from DRI.

3.3. Estimation Results

Table 4 presents the results of estimating equation (9) for each of our eleven metropolitan areas. For comparison purposes, we also estimate a model of retail expenditures similar to the Wheaton-Torto specification, except by metropolitan area. These results are reported in table 5.

Four main findings should be noted. First, for those metropolitan areas in which the income coefficient is significant, the estimated short-run elasticities for the Wheaton-Torto specification are generally in the range of 0.26 to 0.62. The estimated long-run elasticities range from a low of 0.32 to a high 1.55. These long-run elasticities generally conform with the results of Wheaton and Torto (1995).

Long-run income elasticities are somewhat higher in the fully specified reduced-form model, in the 0.57 to 1.76 range, although there were some erratic estimates in certain metropolitan areas (for example, a -1.39 elasticity estimate for Milwaukee-Waukesha). These elasticities are measured in the usual way.[8]

Second, the effect of relative prices in our fully specified reduced-form model are generally positive when significant, although these coefficients are relatively unstable. This implies increases both in producer prices (factor costs) and product prices would tend to increase the total dollar sales volume, suggesting rather price inelastic demand.

Third, although the demographic variables frequently have significant coefficients in both the Wheaton-Torto and fully-specified models, they are occasionally of the wrong sign. The most consistent results are found on the unemployment variable, especially in the Wheaton-Torto model. In the Wheaton-Torto model, the unemployment variable typically enters the regression with a negative and significant sign.

Fourth, the explanatory power of the Wheaton-Torto model is typically significantly better than that of our fully specified reduced-form model, with adjusted R^2s typically between 90.8% and 99.5% (with the exception of Oakland at 74%), as compared to between 56.6% and 95.2% for the fully specified model. This may be deceiving, however, as part of the explanation lies in the conversion to real sales figures from nominal in the reduced-form specification. Coefficients of variation are also typically lower for the Wheaton-Torto specification, and *F*-statistics are higher. The simulations provided below use the Wheaton-Torto specification.

3.4. Forecast Errors

The forecast errors (actual minus predicted sales) associated with the Wheaton-Torto specification are fairly small. The range is from a low of -0.25% per annum in San Diego to a high of 1% per annum in Houston. But, as expected, when the residuals are forecasted over a long period (and when the residuals are not clustered, as in the case of the retail construction starts analyzed in section 3), there are likely to be large positive and large negative forecast errors within each metropolitan area that will cancel each other out. Consequently, we would expect relatively small overall forecast errors.

We also note here that the forecast errors do not bear a significant relation to actual growth rates in retail sales. Two cities, Houston and Atlanta, had positive annual growth rates in retail sales and positive forecast errors. Two cities, St. Louis and Los Angeles, had positive annual growth rates in retail sales, but negative (that is, overly optimistic) forecast errors. One city, San Diego, had a negative annual growth rate in retail sales and a negative forecast error.

4. Vector Autoregressions

4.1. Modeling

We make use here of a VAR model to form expectations of the stock-market returns, the interest rate on commercial mortgages, the inflation rate, and the logarithm of stock market volatility. Our specification follows the recent work of Fama and French (1988), Campbell and Shiller (1988), McQueen and Thorley (1991), and Poterba and Summers (1988), among others. This literature, which we discuss briefly below, suggests that long-horizon stock returns are partially predictable. Further, these studies would appear to justify using knowledge of past returns to predict probable future returns. In this regard, these findings differ considerably from the independence of the random walk theory popularized by Malkiel (1985) and others, which suggests that a series of stock price changes has no memory and that the future path of price level of a security is no more predictable than the path of a series of cumulated random numbers.

The model involves estimating the equation

$$y_t = A_1 y_{t-1} + \cdots + A_n y_{t-n} + \varepsilon_t, \tag{10}$$

where y_t its lagged values, and ε_t are 4 × 1 vectors, and A_1,...,A_n are 4 × 4 matrices of constants to be estimated.

For macroeconomic variables are specified for y_t following the discussion above. First, the stock-market returns are measured by a value-weighted index of NYSE and AMEX stocks. As this return increases in the present, we would expect it to remain large for several quarters while slowly reverting to its historical mean. These expectations conform with McQueen and Thorley (1991), Poterba and Summers (1988), and Fama and French (1988). McQueen and Thorley (1991), and Poterba and Summers (1988) show, for example, that today's below-average returns are followed by above-average future returns, and vice versa. Fama and French (1988) argue that the market risk premium (expected stock return less the return on Treasury bills) is highly autocorrelated but slowly mean reverting. Second, the interest rate on commercial mortgages is taken from commercial mortgage statistics published by the American Council of Life Insurance (ACLI). As has been verified by several empirical studies (see, for example, Sa-Aadu, Shilling, and Wang, 1996), the commercial mortgage rate also shows signs of autocorrelations. This bias increased during the recent decade despite the fact that mortgage markets and capital markets would appear to be much more integrated today. Third, the inflation rate is a consumer price deflator. Inflation obviously is an important part of expected returns. If inflation turns out to be higher than expected, the real return that investors realize will be cut. Fourth, following the lead of French, Schwert, and Stambaugh (1987), the logarithm of stock market volatility is defined as the average squared daily return on the Standard & Poor's Composite Index within the quarter. The evidence suggests that volatility leads expected stock market returns. These findings generally call into question the value of modeling expected returns as a constant function of conditional variance.

The estimation of (10) is straightforward. The estimation is carried out using ordinary least squares. The only problem is that of the choice of lags. We consider three lags for each variable. This means that each equation in our model has twelve parameters to be estimated.

4.2. Empirical Results

Table 6 presents the results of estimating (10). Of primary interest to us here are the explanatory powers of the individual equations. In general, the "explained" variation is quite high, with the obvious exception of the stock-market equation. Certainly, we did not expect to explain a large amount of the variation in stock market returns.

There are several features of the results in table 6 that should be emphasized. One is the effect of the lagged values of inflation on the commercial mortgage rate. One would typically expect that an increase in the rate of price change should lead to an increase in commercial mortgage rates. The results, however, suggest that there is very little positive correlation between the commercial mortgage rate and lagged values of inflation. Moreover, what correlation that does exist between the commercial mortgage rate and lagged values of inflation (and is statistically significant) tends to be negative.

Another seeming anomaly is that there is the positive correlation between the stock market returns and lagged values of inflation. Normally, one would expect realized stock market returns and inflation rates to move in opposite directions.

With respect to the lagged values of the logarithm of stock-market volatility, there are no *t*-ratios in the stock-market-return equation or the commercial mortgage-rate equation in excess of 1. We are at a loss to explain this result. Normally, one would expect a strong positive relation between long-term debt and equity yields, and volatility. We also had expected a positive relation between volatility and realized stock-market returns: the higher the stock-market returns, the greater the volatility, and vice versa.

5. What Moves Retail Property Returns?

5.1. Modeling

We can now consider the estimation of the following model:

$$R = \beta_0 + \beta_1\hat{\zeta}_1 + \beta_2\hat{\zeta}_2 + \beta_3\hat{\zeta}_3 + \beta_4\hat{\zeta}_4 + \beta_5\hat{\zeta}_5 + \beta_6\hat{\zeta}_6 + \varepsilon, \qquad (11)$$

where R is the nominal return on retail properties, and $\hat{\zeta}_i$ is the news components from the two reduced-form equations and four vector autoregressions estimated above.

The specification of (11) allows us to determine how much of the variation in retail property returns is explained by $\hat{\zeta}_1, \ldots, \hat{\zeta}_6$. We can also ask the question, How much can $\hat{\zeta}_1$ and $\hat{\zeta}_2$ explain after $\hat{\zeta}_3, \ldots, \hat{\zeta}_6$ are included in the regression equation? For each of these tests, we compute the R^2 of the equation.

We estimate (11) using NCREIF metropolitan-level returns data for neighborhood and community shopping centers. To correct R for appraisal smoothing, we rely on the procedure developed by Fisher, Geltner, and Webb (1994). This requires some data manipulation on our part that involves applying standard univariate time-series estimation procedures to the smoothed return index for each metropolitan area. The Fisher-Geltner-Webb correction procedure implicitly assumes that the underlying true (that is, unsmoothed) returns are uncorrelated across time. This latter assumption presupposes that real estate markets are weak-form efficient.[9] Needless to say, the assumption of weak-form market efficiency may not be valid for true real estate returns. However, for our purposes the assumption of weak-form market efficiency means that *R* is (arguably) overcorrected for appraisal smoothing. This result is more likely to understate the measure of R^2 for (11) than to overstate R^2 (that is, if we are to err in correcting *R* for appraisal smoothing, we are likely to err on the conservative side).

5.2. Returns on Neighborhood and Community Shopping Centers

The part of *R* that is accounted for by the explanatory variables $\hat{\zeta}_1, \ldots, \hat{\zeta}_6$ is presented in table 7. These results generally suggest that macroeconomic news (that is, innovations in stock-market returns, the interest rate on commercial mortgages, the inflation rate, and the logarithm of stock-market volatility) have little independent significance as a determinant of movements in retail real estate returns. For the unadjusted returns series, the reported R^2s vary from a low of 0.0333 with no lags to a high of 0.0654 with a twelve-quarter lag (see column 1). In comparison, the reported R^2s for the unsmoothed returns vary from a low of 0.0080 with no lags to a high of 0.0353 with a twelve-quarter lag (see column 3).

With respect to our market innovation variables (that is, the innovations in retail construction starts and retail sales), the results in table 7 suggest a modest degree of predictive power. The reported R^2s for the unadjusted returns vary from a low of 0.0700 with no lags to a high of 0.2698 with a twelve-quarter lag (see column 2). In comparison, the reported R^2s for the unsmoothed returns vary from a low of 0.0297 with no lags to a high of 0.2819 with a twelve-quarter lag (see column 4).

Let us now mention a few points that are important enough or intriguing enough to call for further exploration. First, with the possible exception of our contemporaneous regressions, an *F*-test based on the results in columns 4 and 5 does not allow us to reject the null hypothesis that the current and lagged values of $\hat{\zeta}_1$ as a group have no effect on R after $\hat{\zeta}_2$ and $\hat{\zeta}_3$,…, $\hat{\zeta}_6$ are included in the regression equation (with a lag) but does allow us to reject the null hypothesis that the values of $\hat{\zeta}_2$ as a group have no effect on *R.* Both sets of variables generally have a positive effect on *R;* although, the former is obviously statistically insignificant (see table 8).

Second, we find a significant lag effect between $\hat{\zeta}_2$ and *R.* There also are some significant lag effects of unexpected changes in mortgage interest rates and inflation on *R.*

These results raise a difficult question: Does the finding of a significant lag effect imply some sort of informational inefficiency or irrationality in real estate market returns? Some might say yes. This suggestion, however, is immediately subject to criticism (as our reviewer pointed out), since the link between the space market variables on the right side of (11) and *R* is unclear. It is conceivable, for example, that $\hat{\zeta}_1$ should affect *R* with a lag owing to the start-up time required to bring a new shopping center online. Furthermore, $\hat{\zeta}_2$ may affect *R* with a lag owing to percentage rent clauses that require the tenant's sales volume to exceed some specified minimum amount before the percentage rent kicks in.

6. Which Markets are the Most Predictable?

The final piece of the puzzle is to say something about which markets are the most predictable. This byproduct makes our model of great interest to practitioners and academics alike. Our analysis proceeds as follows. First, we use (11) to estimate forecasting errors for the unadjusted retail real estate returns for each metropolitan area. Then we estimate how much of the variation in *R* for each metropolitan area can be explained by $\hat{\zeta}_1$,..., $\hat{\zeta}_6$ by dividing the residual sum of squares by the total sum of squares for each metropolitan area and subtracting the quotient from 1. We then repeat this process using the unsmoothed retail real estate returns.

The results, reported in table 9, suggest that there are significant differences in predictability across the different markets. For the unadjusted returns series, the reported R^2s vary from a low of zero in Atlanta and St. Louis (with no lags) to a high of 0.3986 in Houston (with a twelve-quarter lag). In comparison, the reported R^2s for the unsmoothed returns vary from a low of 0.0201 in Atlanta (with no lags) to a high of 0.4578 in Houston (with a twelve-quarter lag). Of course, the question is whether this is about the right magnitude and whether a high R^2 means that one metropolitan area is more predictable (that is, more informationally inefficient) than another. Just looking at the reported R^2s associated with the contemporaneous effects of $\hat{\zeta}_1$,...,$\hat{\zeta}_6$ on *R,* we see that where returns are high, R^2s are below average (that is, greater uncertainty). Likewise, where returns are low, R^2s appear to be above average (that is, lower uncertainty). For the unadjusted return series, for example, the mean quarterly return in those metropolitan areas with an above-average R^2 is 1.019; and in those metropolitan areas with a below-average R^2 the mean return is 1.016.[10] For the unsmoothed return series, the respective mean returns are 1.019 and 1.017.[11] Lastly, we can see from columns 5 and 7 of table 9 that there are significant lagged effects among the various metropolitan areas (which again begs the question of whether these markets are informational inefficient).

7. Conclusions

This article has developed, estimated, and simulated a six-equation model of retail construction starts, retail sales, stock-market returns, commercial mortgage rates, inflation, and the logarithm of stock-market volatility. Estimation was consistent with the theory and provided close fits in all cases. Residuals from these equations were then used to explain the movement in the NCREIF retail property return index.

Our principal reason for focusing on the NCREIF retail property return index is its importance to investment advisors and other investors. Almost all–perhaps all–real estate investment and portfolio decisions made by large pension funds, banks, and insurance companies are founded on appraisal-based real estate returns. Note also that our model is similar in spirit to recent analyses of stock-market returns. We address the issue of what causes retail property returns to move by explicitly relating the NCREIF retail property return index at the metropolitan level to the underlying determinants of supply and demand for retail real estate.

The results indicated that less than 3% of the variance in unsmoothed appraisal-based retail real estate returns can be explained by contemporaneous macroeconomic news and market innovations. The results showed also that augmenting the model with lagged values significantly improved its fit. With lags of up to three years, the explained variation in unsmoothed appraisal-based retail real estate returns increased to 28% (with most of the improvement in fit coming from the addition of lagged values of unexpected changes in retail starts and retail sales).

The results also indicated that some metropolitan areas are more predictable than other metropolitan areas. The reported R^2s vary from 0.0201 for Atlanta (with no lags) to 0.4579 for Houston (with lags of up to three years).

These findings raise some interesting questions. For example, does the existence of a lag effect indicate informational inefficiency in real estate market returns? Or is there a natural lagged relationship between the space markets and the asset market? Unhappily, we have, as of yet, little theory that can be used to answer these questions. Moreover, what theory we do have is inconclusive with respect to the formal link between space markets and asset markets.

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Notes

1. Summers (1995) likens such tests to testing whether the price of one-quart ketchup bottles bears the hypothesized relationship to the price of one-pint ketchup bottles. He argues that, in the study of the ketchup market, one should attempt to explain the price of ketchup in terms of such factors as wages, the price of tomatoes, the income of consumers, the price of hamburgers, the price of mustard, and so on. Our interests lie in explaining retail property returns in terms of fundamental economic variables.
2. One might also argue that certain retail properties may even benefit from a positive supply change. There may be markets, for example, where the positive supply change brings about increased agglomeration benefits (that is, where there are real unit cost savings to consumers brought about by the increased supply of retail space within the market). In which case, a positive supply change may cause rent levels to rise as opposed to fall.
3. As in the case of residential properties, the demand for retail properties is closely associated with the size, type, and location of the population. In our model, retail sales are directly affected by how much money the population has to spend and by the number of people in the area.
4. In our estimations, we also included a series of 0-1 variables to account for any possible seasonalities in shopping center construction starts.
5. The equations appear to suffer from substantial autocorrelation, but this is deceiving. Examination of the residuals from (6) reveals a distinct clustering. This phenomenon follows from the nature of the data. The quarter-to-quarter changes in shopping center construction starts are frequently significant, especially when large regional shopping center developments are undertaken. For example, when the Mall of America development in the Minneapolis MSA was started, there was a large single-quarter increase for that quarter, while in subsequent quarters there was a large single-quarter drop in shopping center construction starts.
6. The 1980s were less than favorable to the U.S. commercial real estate industry. Estimates by Giliberto (1992) suggest that nearly 1 billion square feet of excess commercial real estate space was built during the 1980s. Similar results are suggested by Hendershott and Kane (1992). Most of this excess construction occurred between 1978 and 1988. In late 1989 and 1990, construction and mortgage lending declined markedly.
7. These include such time series techniques as Box-Jenkins and Holt-Winters adaptive

forecasting techniques (see Mathews and Diamantopoulos, 1989), Box-Cox models, state-space models (see Gross and Sohl, 1989), exponential smoothing (see Gross and Sohl, 1989), ARIMA models (see Watson, Pastuszek, and Cody, 1987), and econometric models making use of substantial cross-sectional information (see Watson, Pastuszek, and Cody, 1987; Dawood and Neale, 1993). Results seem to vary widely, depending on the particular purpose and characteristics of the data.

8. We calculate the short-run and long-run elasticities as $\eta_{SR} = \alpha_1$ and $\eta_{LR} = \alpha_1/(1-\alpha_6)$, respectively.
9. We also have corrected *R* for appraisal smoothing following the procedure in Geitner (1993), which allows one to recover an estimate of the underlying market return from publicly reported appraisal-based returns by assuming appraisal-based returns follow a first-order autoregressive transfer function with exponentially declining lag weights. The results of these tests are available on request.
10. For the unadjusted return series, cities with below-average R^2s include Atlanta, Detroit, Houston, Los Angeles, and St. Louis; and cities with above-average R^2s include Chicago, Minneapolis, and Tampa.
11. For the unsmoothed return series, cities with below-average R^2s include Atlanta, Chicago, Los Angeles, and Tampa; and cities with above-average R^2s include Detroit, Houston, Minneapolis, and St. Louis.

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Appendix
Table 1
Selected Characteristics of the data

Metropolitan Statistical Area (MSA)	Average Annual Shopping Center Starts[a] (in 000 s.f.)	Average Annual Shopping Center Removals (in 000 s.f.)	Average Annual Net Growth in Square Feet of Shopping Center Space	Average Annual Real Growth in Shopping Center Sales	Average Annual Real Growth in Shopping Center Sales per Square Foot	Time Frame of the Analysis (Quarter/Year)
Atlanta	2304	416	4.05%	5.52%	0.88%	1/78–2/94
Chicago	3160	1436	1.69%	0.69%	− 0.78%	1/78–2/94
Detroit	1484	652	1.58%	2.54%	0.77%	1/78–2/94
Houston	1960	480	4.02%	1.63%	− 1.44%	1/78–2/94
Los Angeles–Long Beach	2588	1220	1.75%	1.43%	− 0.25%	1/78–2/94
Milwaukee	360	192	0.98%	0.12%	− 0.74%	1/78–2/94
Minneapolis	1120	580	1.55%	1.98%	0.34%	1/78–2/94
St. Louis	572	316	0.89%	3.89%	2.62%	1/78–2/94
San Diego	1012	304	4.79%	1.68%	− 1.74%	1/78–2/94
Oakland	788	328	2.01%	2.87%	0.75%	1/87–2/94
Tampa–St. Petersburg	1476	272	3.68%	6.18%	1.95%	1/87–2/94

Note: All data supplied by DRI/F.W. Dodge. At the time this study was conducted, retail sales were not collected by DRI at the MSA level for Dallas, Denver, Orange County (CA), Portland (OR), Sacramento, and San Jose, where companion data was available, which significantly limited the number of MSAs tested. Additionally, for the Oakland and Tampa-St. Petersburg MSAs, retail data at the MSA level was first available the first quarter of 1987.

[a] Shopping center starts generally include all retail developments where there is a clustering of two or more retailers on one site. For instance, a stand-alone WalMart with a stand-alone Wendy's on an out pad would not be considered a shopping center. On the other hand, if that same WalMart were located in a center with several other contiguous retailers the development would be considered a shopping center.

Table 2
Estimates of retail construction starts dependent variable: Quarterly retail construction starts (*t*-statistics reported in parenthesis)

Metropolitan Statistical Area (MSA)	Intercept	c_0	c_1	c_2	Quarter 1	Quarter 2	Quarter 4	d_0	d_1	d_2	R^2
Atlanta	275,016	0.000767	0.000195	0.000102	– 63,154	– 51,470	204,296	0.5183	– 0.3959	0.4313	0.77
	(1.81)	(4.64)	(1.03)	(0.33)	(– 0.49)	(– 0.38)	(1.57)	(1.28)	(– 1.32)	(1.83)	
Chicago	561,928	0.000760	– 2.4257	– 0.000011	– 316,578	– 96,646	– 72,089	0.3747	– 0.05078	– 0.1908	0.38
	(2.57)	(3.45)	(– 0.01)	(– 0.03)	(– 1.26)	(– 0.40)	(– 0.31)	(2.11)	(– 0.18)	(– 0.60)	
Detroit	260,911	0.000660	0.000317	– 0.000203	– 213,052	31,463	– 153,728	0.5105	0.2392	– 0.2154	0.56
	(2.68)	(5.57)	(1.87)	(– 1.36)	(– 2.19)	(0.32)	(– 1.58)	(3.03)	(1.13)	(– 0.86)	
Houston	199,627	– 0.000032	0.000178	– 0.000071	102,966	115,207	71,857	0.7269	– 0.6410	0.4360	0.32
	(1.70)	(– 0.07)	(0.69)	(– 0.34)	(0.64)	(0.73)	(0.45)	(4.00)	(– 1.88)	(1.25)	
Los Angeles–Long Beach	487,299	0.000553	0.000053	– 0.000154	– 124,910	30,703	– 137,959	0.2591	0.3260	0.0242	0.48
	(3.17)	(4.77)	(0.39)	(– 1.07)	(– 0.90)	(0.21)	(– 0.99)	(1.63)	(1.56)	(0.12)	
Milwaukee	132,901	0.000693	0.000547	– 0.000431	– 31,702	63,879	– 12,693	0.4824	0.5400	– 0.0773	0.65
	(2.21)	(3.66)	(1.55)	(– 1.82)	(– 0.52)	(0.95)	(– 0.23)	(1.01)	(0.75)	(– 0.16)	
Minneapolis	265,000	0.000386	0.000138	0.000341	– 37,296	15,614	– 54,030	– 0.0100	– 0.6134	– 0.3141	0.48
	(1.11)	(1.75)	(0.50)	(0.92)	(– 0.33)	(0.12)	(– 0.48)	(– 0.02)	(– 1.67)	(– 0.66)	
Oakland	2,510,419	0.002340	– 0.000253	– 0.000869	– 310,272	– 274,484	– 231,527	– 0.0525	0.00871	0.00325	0.44
	(2.52)	(2.26)	(– 0.49)	(– 1.33)	(– 1.19)	(– 1.22)	(– 1.15)	(– 2.23)	(0.70)	(0.26)	
St. Louis	98,879	0.000213	0.000181	– 0.000059	88,053	24,392	28,011	– 0.00101	– 0.00565	– 0.00034	0.19
	(2.02)	(1.73)	(1.23)	– 0.38)	(1.60)	(0.44)	(0.49)	(– 0.77)	(– 1.19)	(– 0.07)	
San Diego	424,097	0.000402	0.000971	0.000368	4,462	120,121	140,425	– 1.7854	– 0.2853	0.3919	0.32
	(2.22)	(1.12)	(1.85)	(1.06)	(0.02)	(0.54)	(0.70)	(– 1.71)	(– 0.84)	(1.47)	
Tampa–St. Petersburg	215,984	0.000352	– 0.000338	0.0000277	98,539	– 201,331	69,707	0.1187	– 0.0861	– 0.0366	0.45
	(3.03)	(2.20)	(– 2.42)	(0.32)	(1.05)	(– 2.24)	(0.75)	(1.78)	(– 0.89)	(– 0.40)	

Table 3
Responses to lagged changes in retail sales parameter estimates (*t*-statistics reported in parenthesis)

	Number of Lags (in Quarters)									
Metropolitan Statistical Area	0	1	2	3	4	5	6	7	8	9
Atlanta	0.0199	0.0185	0.0180	0.0184	0.0196	0.0218	0.0248	0.0287	0.0335	0.0392
	(1.02)	(1.78)	(2.53)	(2.07)	(1.87)	(2.10)	(2.88)	(3.84)	(2.80)	(1.81)
Chicago	0.0235	0.0239	0.0242	0.0244	0.0245	0.0244	0.0243	0.0241	0.0237	0.0233
	(0.77)	(1.30)	(2.10)	(2.21)	(1.92)	(1.84)	(2.00)	(2.18)	(1.64)	(0.96)
Detroit	− 0.0052	0.0052	0.0139	0.0209	0.0262	0.0297	0.0314	0.0314	0.0296	0.0260
	(− 0.41)	(0.61)	(2.28)	(3.61)	(4.18)	(4.60)	(5.08)	(5.15)	(3.95)	(2.34)
Houston	− 0.0068	− 0.0125	0.0113	− 0.0057	0.0016	0.0082	0.0113	0.0085	− 0.0029	—
	(− 0.27)	(− 0.71)	(− 0.61)	(− 0.31)	(0.09)	(0.45)	(0.61)	(0.49)	(− 0.12)	
Los Angeles–Long Beach	0.0068	0.0128	0.0174	0.0207	0.0226	0.0232	0.0224	0.0203	0.0168	0.0121
	(0.61)	(1.86)	(3.54)	(4.10)	(4.00)	(3.99)	(4.08)	(3.68)	(2.32)	(1.08)
Milwaukee	− 0.0277	− 0.0067	0.0106	0.0241	0.0339	0.0339	0.0422	0.407	0.0355	0.0265
	(− 1.26)	(− 0.44)	(0.91)	(2.24)	(3.07)	(3.58)	(3.81)	(3.42)	(2.34)	(1.23)
Minneapolis	− 0.0034	0.0217	0.0276	0.0206	0.0071	− 0.0065	− 0.0140	− 0.0091	0.0146	0.0635
	(− 0.13)	(1.37)	(1.81)	(1.52)	(0.60)	(− 0.48)	(− 0.85)	(− 0.55)	(0.85)	(1.88)
Oakland	0.0412	0.0686	0.0885	0.1009	0.1056	0.1029	0.0925	0.0746	0.0491	0.0161
	(0.79)	(1.71)	(2.24)	(2.31)	(2.24)	(2.18)	(2.12)	(2.02)	(1.58)	(0.46)
St. Louis	− 0.0053	− 0.0013	0.0023	0.0053	0.0078	0.0098	0.0113	0.0123	0.0127	0.0127
	(− 0.42)	(− 0.16)	(0.38)	(0.90)	(1.24)	(1.58)	(2.02)	(2.32)	(1.80)	(1.11)
Tampa–St. Petersburg	0.0262	0.0230	0.0199	0.0170	0.0142	0.0115	0.0089	0.0065	0.0041	0.0019
	(2.31)	(2.40)	(2.60)	(2.56)	(2.33)	(1.98)	(1.58)	(1.20)	(0.83)	(0.44)
San Diego	− 0.0139	− 0.0158	− 0.0160	− 0.0146	− 0.0115	− 0.0067	− 0.0004	0.0077	0.0173	0.0286
	(− 0.99)	(− 0.89)	(− 0.97)	(− 0.89)	(− 0.70)	(− 0.42)	(− 0.02)	(0.53)	(1.22)	(1.81)

Table 4
Estimation results: Sales forecasting model–full specification, dependent variable–log *S*

	Parameter Estimates (Standard Error)										
Variable	Atlanta	Chicago	Detroit	Houston	Los Angeles–Long Beach	Milwaukee	Minneapolis–St. Paul	Oakland	St. Louis	San Diego	Tampa–St. Petersburg
Intercept	—	36.38**	– 29.72	10.89	0.230	90.165**	—	– 16.980	53.993**	– 34.660**	36.692**
		(10.76)	(34.00)	(9.63)	(6.504)	(23.437)		(25.450)	(22.982)	(14.893)	(14.630
$\log(P_R/P)$	—	0.0532	0.183	0.389**	0.116	0.688	—	– 0.115	0.196	– 0.00255	0.386**
		(0.0998)	(0.213)	(0.167)	(0.102)	(0.431)		(0.393)	(0.201)	(0.25057)	(0.176)
$\log Y$	—	0.826**	1.414**	0.224	0.575**	– 0.400*	—	0.678	0.182	1.266**	0.595**
		(0.307)	(0.423)	(0.530)	(0.102)	(0.747)		(1.030)	(0.332)	(0.215)	(0.258)
$\log HH$	—	– 1.803**	2.369	0.655	0.321	– 4.707**	—	0.653	– 1.416	2.308**	– 0.700
		(0.770)	(2.317)	(0.778)	(0.394)	(1.313)		(1.276)	(1.438)	(0.704)	(1.042)
$\log(d1)$[a]	—	1.987**	– 0.180	2.576	0.330	11.134**	—	– 2.877	– 2.306**	– 2.022**	6.738**
		(0.642)	(0.852)	(1.600)	(0.268)	(4.303)		(2.857)	(0.997)	(0.791)	(0.814)
$\log(d2)$[b]	—	– 1.223	– 0.255	0.418	– 1.053**	– 9.189**	—	– 3.028	5.868**	– 4.833*	0.829
		(0.821)	(1.055)	(0.605)	(0.410)	(4.325)		(3.808)	(1.974)	(2.675)	(1.144)
$\log(d3)$[c]	—	– 0.000946	– 0.00860	0.140**	– 0.0446**	– 0.346**	—	– 0.0115	– 0.113**	– 0.1389	– 0.196**
		(0.032787)	(0.05131)	(0.066)	(0.0207)	(0.091)		(0.1109)	(0.049)	(0.0443)	(0.043)
$\log(P_P/P)$	—	– 0.361	– 0.141	0.794*	0.453**	1.826**	—	0.540	0.580*	– 0.2046	– 0.0633
		(0.282)	(0.375)	(0.438)	(0.127)	(0.740)		(0.913)	(0.339)	(0.1256)	(0.3232)
$\log(S_1)$	—	0.221	0.200	0.210	0.463**	– 0.0108	—	0.632**	– 0.206	0.00540	– 0.419
		(0.172)	(0.176)	(0.158)	(0.093)	(0.2008)		(0.196)	(0.192)	(0.00781)	(0.0507)
R^2	—	0.702	0.905	0.682	0.951	0.926	—	0.735	0.786	0.963	0.955
Adj. R^2	—	0.607	0.874	0.566	0.943	0.898	—	0.629	0.717	0.952	0.948
Dependent mean	—	23.349	22.888	22.597	23.515	21.662	—	22.142	22.326	22.080	22.438
Coefficient variable	—	0.07220	0.08590	0.12174	0.07748	0.14254	—	0.17355	0.08123	0.10504	0.14155
F-value	—	7.362**	29.603**	5.885**	121.410**	32.929**	—	6.922**	11.452**	81.913**	132.135**
Durbin–Watson	—	2.130	2.337	1.825	1.655	1.958	—	1.462	2.251	1.785	0.718

[a] *d*1 = % population between 35 and 55.
[b] *d*2 = % population 65 and older.
[c] *d*3 = unemployment rate.
*Significant at the 10% level.
**Significant at the 5% level.

Table 5
Estimation results: Sales forecasting model–Wheaton-Torto specification, dependent variable–log *S* (all values measured in current dollars)

	Parameter Estimates (Standard Error)										
Variable	Atlanta	Chicago	Detroit	Houston	Los Angeles–Long Beach	Milwaukee	Minneapolis–St. Paul	Oakland	St. Louis	San Diego	Tampa–St. Petersburg
Intercept	1.947	10.921**	−1.380	12.800**	4.509**	3.973**	−2.311	−3.899	21.131**	−2.116	2.305
	(1.954)	(2.967)	(7.958)	(4.261)	(1.724)	(1.608)	(1.779)	(6.116)	(8.379)	(1.383)	(1.670)
$\log(Y \times HH)$	0.544**	0.262**	0.596	0.0310	0.272**	0.195*	0.546**	0.883	−0.0940	0.620**	0.157
	(0.168)	(0.119)	(0.386)	−0.1371	(0.088)	(0.102)	(0.177)	(0.526)	(0.3844)	(0.144)	(0.100)
$\log(d1)$[a]	−0.318**	0.165**	−0.135**	0.188	0.0510	−0.0375	−0.192**	−0.487	−0.171**	−0.215**	0.350**
	(0.123)	(0.063)	(0.053)	(0.148)	(0.0343)	(0.0918)	(0.079)	(0.316)	(0.056)	(0.062)	(0.106)
$\log(d2)$[b]	−0.488	0.373	0.120	0.761*	−0.378**	0.251	−0.422	−1.576	2.242**	0.202	0.0970
	(0.605)	(0.318)	(0.367)	(0.426)	(0.159)	(0.355)	(0.542)	(1.421)	(0.880)	(0.262)	(0.1722)
$\log(d3)$[c]	0.0105	0.00617	−0.0103	0.0797**	−0.0344**	−0.0328**	−0.0469	−0.0928	−0.0731	−0.0760**	−0.0993**
	(0.0322)	(0.01403)	(0.0212)	(0.0323)	(0.0086)	(0.0158)	(0.0376)	(0.0590)	(0.0278)	(0.0162)	(0.0235)
$\log S_1$	0.516**	0.182	0.469**	0.301*	0.559**	0.607**	0.647**	0.607**	−0.0313	0.504	0.623**
	(0.158)	(0.171)	(0.189)	(0.161)	(0.095)	(0.114)	(0.125)	(0.159)	(0.1798)	(0.097)	(0.097)
R^2	0.966	0.982	0.980	0.924	0.995	0.978	0.983	0.786	0.979	0.991	0.964
Adj. R^2	0.960	0.979	0.977	0.908	0.995	0.976	0.981	0.739	0.976	0.990	0.961
Dependent mean	23.837	24.649	24.197	23.991	24.674	22.889	23.702	23.530	23.635	23.370	23.765
Coefficient variable	0.10130	0.06338	0.08560	0.11370	0.07913	0.14388	0.09651	0.15465	0.07776	0.11750	0.10371
F-value	160.311**	308.551**	279.642**	60.405*	2146.886**	473.580**	332.503**	16.893**	265.167**	1222.460**	286.860**

[a] $d1$ = % population between 35 and 55.
[b] $d2$ = % population 65 and older.
[c] $d3$ = unemployment rate.
$d1$-$d3$ are scaled multiplicatively by 1n(Y x HH)
*Significant at the 10% level.
**Significant at the 5% level.

Table 6
VAR estimation results (*t*-statistics reported in parentheses) (quarterly 1978:1 to 1994:2)

		Independent Variables												
Dependent Variable	Intercept	Stk Mkt Ret_{-1}	Stk Mkt Ret_{-2}	Stk Mkt Ret_{-3}	Mtg $Rate_{-1}$	Mtg $Rate_{-2}$	Mtg $Rate_{-3}$	Inf_{-1}	Inf_{-2}	Inf_{-3}	Vol_{-1}	Vol_{-2}	Vol_{-3}	R^2
Stock market	−0.090	−0.088	−0.224	−0.222	−3.070	−0.460	4.490	0.123	0.431	0.325	0.062	0.043	−0.043	0.18
return[a]	(−1.3)	(−0.7)	(−1.7)	(−1.7)	−1.1)	(−0.1)	(1.6)	(0.5)	(1.5)	(1.2)	(1.1)	(0.8)	(−0.7)	
Commercial	0.007	−0.004	0.005	0.011	1.259	−0.046	−2.75	−0.001	0.012	0.012	−0.003	−0.001	0.002	0.97
mortgage rate	(2.0)	(−0.6)	(0.9)	(1.7)	(9.3)	(−0.2)	(−2.0)	(−0.1)	(0.8)	(0.9)	(−1.1)	(−0.3)	(0.5)	
Inflation rate	0.035	0.059	0.070	−0.027	2.040	−1.003	−1.065	−0.574	0.059	0.007	−0.008	0.022	−0.051	0.42
	(1.0)	(1.1)	(1.1)	(−0.4)	(1.5)	(−0.5)	(−0.7)	(−4.4)	(0.4)	(0.1)	(−0.3)	(0.8)	(−1.8)	
Stock market	0.213	0.434	0.047	0.360	−2.957	7.041	−5.316	−0.133	−0.336	0.185	0.290	0.257	0.254	0.65
volatility logarithm	(1.4)	(1.5)	(0.2)	(1.2)	(−0.5)	(0.7)	(−0.9)	(−0.2)	(−0.5)	(0.3)	(2.3)	(2.0)	(2.0)	

[a]Value-weighted return index of NYSE and AMEX stocks.

Table 7
Fitted models of appraisal-based retail real estate returns explained variation (R^2)

	Unadjusted Returns			Unsmoothed Returns		
Number of Lags (in Quarters)	(1) Macroeconomic News Events Only	(2) Macroeconomic News Events and Market Innovations	(3) Macroeconomic News Events Only	(4) Macroeconomic News Events and Market Innovations	(5) All Variables Except Unexpected Retail Starts	(6) All Variables Except Unexpected Retail Sales
0	0.0333	0.0700	0.0080	0.0297	0.0208	0.0211
4	0.0512	0.0987	0.0293	0.1148	0.0782	0.0637
8	0.0579	0.1937	0.0296	0.1526	0.1361	0.0830
12	0.0654	0.2698	0.0353	0.2819	0.2287	0.0931

Table 8

Estimates of fully specified model of appraisal-based real estate returns, dependent variable–quarterly retail real estate returns (*t*-statistics reported in parentheses)

	Number of Lags (in Quarters)							
	Using Unadjusted Returns				Using Unsmoothed Returns			
	0	4	8	12	0	4	8	12
dRetail Starts	1.29E-08	6.81E-09	7.33E-09	2.20e-09	3.09E-08	7.99E-09	1.79E-08	1.86E-09
	(1.0)	(0.8)	(0.9)	(0.3)	(1.0)	(0.2)	(0.6)	(0.2)
dRetail Sales	− 2.55E-07	− 2.86E-07	− 1.12E-06	1.74E-06	− 3.91E-06	1.07E-06	− 5.72E-06	8.70E-06
	(− 0.2)	(− 0.2)	(− 0.7)	(1.3)	(− 0.8)	(0.3)	(− 1.0)	(1.8)
dStkMktRet	− 0.13	0.01	0.02	0.001	− 0.22	0.06	0.09	0.04
	(− 2.0)	(0.1)	(0.4)	(0.01)	(− 0.9)	(0.3)	(0.5)	(0.2)
dMtgRate	− 0.18	− 0.38	1.52	− 3.22	0.96	− 1.52	4.71	− 13.13
	(− 0.1)	(− 0.3)	(1.2)	(− 2.3)	(0.2)	(− 0.3)	(1.0)	(− 2.5)
dInf	0.38	− 0.13	− 0.18	0.12	0.98	− 1.22	− 0.32	0.25
	2.5	− 1	− 1.5	0.9	1.8	− 2.6	− 0.7	0.5
dVol	− 0.003	0.03	0.05	− 0.01	− 0.12	− 0.01	0.02	− 0.19
	(1.0)	(1.5)	(− 0.4)	(− 0.2)	(− 1.0)	(− 0.1)	(0.2)	(− 1.7)

dRetail Starts = unanticipated change in retail starts.
dRetail Sales = unanticipated change in retail sales.
dStk Mkt Return = unanticipated change in stock market return.
dMtg Rate = unanticipated change in commercial mortgage rate.
dInf = unanticipated change in inflation.
dVol = unanticipated change in stock market volatility.

Table 9
Explained variance of appraisal-based retail real estate returns, by metropolitan area

				Using Unadjusted Returns		Using Unsmoothed Returns	
	Mean Quarterly Return, %	Unadjusted Standard Deviation	Unsmoothed Standard Deviation	R^2 No Lags	R^2 3-yr Lags	R^2 No Lags	R^2 3-yr Lags
Atlanta	1.022	0.0299	0.0913	0	—	0.0201	—
Chicago	1.019	0.0244	0.0759	0.1080	0.0981	0.0258	0.2939
Detroit	1.014	0.0282	0.0869	0.0084	0.1585	0.0811	0.2094
Houston	1.020	0.0392	0.1564	0.0261	0.3986	0.0367	0.4579
Los Angeles	1.029	0.0320	0.0780	0.0246	—	0.0268	—
Minneapolis	1.021	0.0316	0.0687	0.2775	—	0.2148	—
St. Louis	1.014	0.0321	0.1122	0	—	0.1069	—
Tampa	1.009	0.3903	0.1094	0.1365	0.3810	0.0205	0.3889