Commercial Real Estate Return Cycles: Do Capital Flows Matter?

by

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March 2006
Revised December 2006

We thank the Real Estate Research Institute for providing partial funding for this project and Mark Zandi of Economy.com for providing metro-level economic data. We also thank participants at the 2006 AREUEA International meeting in Vancouver for helpful comments and suggestions.

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Abstract

This paper examines the short- and long-run dynamics among institutional capital flows and returns in private real estate markets. The main tool of analysis we employ is a vector autoregressive (VAR) regression model in which both institutional capital flows and returns are specified as endogenous variables in a two equation simultaneous system and in which we also control for various financial and economic variables. When aggregating across U.S. CBSAs and property types, we find some evidence that both lagged NCREIF returns and lagged NCREIF flows significantly influence current returns. However, these aggregate results mask significant cross-sectional variation across different metropolitan areas and property types. In particular, we provide evidence that our aggregate results are driven by a limited number of large CBSAs. We find no evidence that returns are predictive of future NPI capital flows. We also document that institutional capital are not generally predictive of relative future capital flows.

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Introduction

A question that has received significant attention in the finance literature is the extent to which exogenous shifts in the demand for individual securities affect valuations and returns. Assuming investor rationality and costless arbitrage, asset prices in public markets are not affected by capital flows or trading activity; the current market value of an asset is simply the present value of the expected future cash flows. However, in recent years a growing behavioral finance literature has been critical of the assumptions of investor rationality and costless arbitrage implied by the efficient market hypothesis. Numerous theoretical models have been developed that assume limited arbitrage (supply inelasticity) and/or heterogeneous investor beliefs ("noise traders"). In these models, investor sentiment, capital flows, and trading volume can have a role in the determination of asset prices—independent of market fundamentals.[1]

The role of capital flows in public market asset pricing has also been the subject of numerous empirical investigations, including analyses of the price impact associated with a stock's inclusion in the S&P 500 or other stock indices, the effects of increased foreign capital flows on stock price valuations in developing countries, and the role of mutual fund capital flows in the asset price movements of individual securities and indices.[2] Although the issue is far from settled, several studies suggest a role for capital flows in the pricing of publicly traded stocks and bonds.

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[1] See Clayton (2003) for a review of the literature that posits and tests for supply and demand effects in the determination of asset prices.

[2] Prior studies that have examined these various effects of capital flows in asset pricing include the following: for stock index studies, see Cha and Lee (2001) and Shleifer (1986); for the effects of foreign capital flows, see Cho, Kho and Stulz (1999), Bekaert and Harvey (2000), Berkaert, Harvet, and Lumsdaine (2002), Brennan and Cao (1997), Stultz (1999), and Tesar and Werner (1995); for the role of mutual fund flows, see Edelen and Warner (2001), Fortune (1998), Karceski (2002), Remolona, Kleiman, and Gruenstein (1997), Sirri and Tufano (1998), and Warther (1995).

The conventional wisdom among real estate practitioners is that capital flows directly impact both liquidity *and* property prices.[3] However, the limited empirical research on this issue does not support this widely held belief. Ling and Naranjo (2003) analyze the influence of total equity flows into the REIT sector on aggregate REIT prices and returns and, simultaneously, the influence of past industry-level returns on subsequent capital flows into the REIT sector. Ling and Naranjo (2006) examine the interrelationships and short- and long-run dynamics between aggregate capital flows to dedicated REIT mutual funds and industry-level REIT returns. No consistent evidence that capital flows are associated with subsequent returns in the REIT sector is uncovered in either study.

The focus of prior stock, bond, and real estate capital flow studies on publicly traded securities is not surprising given the availability of flow and return data in public markets. However, the lack of a rigorous analysis of the dynamics of capital flows and returns in private real estate markets is a serious void in the literature for several reasons. First, real estate practitioners have long argued that the relation between capital flows and property prices is more pronounced and intense in private markets that lack the liquidity and supply elasticity of public markets. Second, approximately 90 percent of investible commercial real estate in the U.S. is owned and traded in private markets.[4] Third, unlike the listed shares of a firm "for which close substitutes exist either directly or indirectly" (Scholes, 1972), the unique location attributes of commercial real estate assets severely restrict an investor's set of acceptable substitutes. In addition, the long lead time required by developers to respond to shortages in a local real estate

[3]In fact, the significant reduction in capitalization rates that occurred in most commercial real estate markets during the first half of the current decade is largely, if not entirely, attributed to the surge in real estate capital flows that occurred during this period. See, for example, Downs (2004) and House (2004).
[4] See Ling and Archer (2008), Chapter 18, page 453.

market may ensure that property prices exceed replacement costs for a sustained period of time. In short, the supply inelasticities inherent in under built and overbuilt commercial real estate markets should, in theory, make asset prices and returns in these markets more susceptible to exogenous demand shocks.

This paper seeks to understand the short- and long-run dynamics among institutional capital flows and real estate returnsin private commercial real estate markets. We begin with an analysis using institutional capital flows and returns aggregated across U.S. markets and property types. However, because increases or decreases in capital flows may have differential effects across geographic segments of the private real estate market, we also disaggregate our analysis by major metropolitan areas. In particular, we first examine whether the capital invested in 43 core business statistical areas (CBSAs) by members of the National Council of Real Estate Investment Fiduciaries (NCREIF) is associated with higher, or lower, property returns and capital flows in subsequent periods. Simultaneously, we examine whether quarterly real estate returns and capital flows in CBSAs, as measured by the NCREIF Property Index (NPI), are predictive of future institutional returns and capital flows by NCREIF members in these CBSAs.

For each metropolitan area, our dynamic analysis is first performed by aggregating CBSA-level capital flows and returns across all commercial property types. However, it is possible that even CBSA-level results mask variation by property type within a given metropolitan area. We therefore examine the short- and long-run dynamics among CBSA capital flows and returns disaggregated by the four major property types: office, industrial, retail, and apartment.

The main tool of analysis we employ is a vector autoregressive (VAR) regression model in which both NCREIF capital flows and returns are specified as endogenous variables in a two equation simultaneous system. We also include other exogenous variables, such as the Fama-French risk factors, changes in interest rates, building starts, employment and per capita income, in an attempt to purge the capital flows and returns equations of the relationship that may exist among the two because of their mutual relation to these exogenous variables and risk factors.

Our primary findings can be summarized as follows. In the aggregate, we find evidence that both lagged returns and lagged flows are predictive of current institutional returns. However, these aggregate U.S. results mask significant cross-sectional variation among metropolitan areas and property types. In fact, we provide evidence that our aggregate results are driven by a limited number of large CBSAs. This suggests that the prediction of CBSA-level returns and flows is, at best, a difficult task. The lack of explanatory power displayed by NCREIF flows in the CBSA return regressions is also robust with respect to disaggregation by property type.

The remainder of the paper proceeds as follows. In the next section, we discuss the theoretical considerations important to the implementation and interpretation of our empirical analysis. We then describe our data sources and provide a discussion of the descriptive statistics. The VAR methodology we employ to examine the conditional covariation of fund flows and returns is then described. In the next section, we present our aggregate results (our CBSA-level results aggregated across property types) and the results produced when we disaggregate the CBSA-level analysis by separately estimating VARs for each of the major property types within our sample of CBSAs. We then discuss the results from various alternative specifications that demonstrate the robustness of our findings. Our conclusions are presented in the final section.

Theoretical Considerations

Finance theory posits that in complete and efficient markets the supply of assets with particular risk/return characteristics is infinitely elastic. Thus, an asset cannot sell for more, or less, than the marginal cost of replicating the risk/return characteristics of the asset's income stream. This, in turn, is equivalent to stating that the market value of an asset is equal to the risk adjusted present value of the expected future cash flows. Thus, under the efficient market hypothesis capital flows do not have a role in asset valuation, nor do valuations and returns have a role in the determination of subsequent capital flows. Given the absence of an alternative theory that posits a dynamic relation between capital flows and asset prices, we rely on vector autoregressions (VARs) to capture and characterize any empirical relations that may exist.

It is important to emphasize that an observed contemporaneous correlation between capital flows into the private commercial real estate sector and underlying asset values and returns is not sufficient to conclude that capital flows affect valuations. An alternative explanation is that fundamental economic variables and risk factors — such as per capita income, employment, and interest rates — produce changes in expected cash flows or required rates of returns which, in turn, lead to both higher asset prices *and* capital flows (Gompers and Lerner, 2000; Clayton, 2003; Ling and Naranjo, 2006). In our empirical work, we include exogenous macroeconomic and CBSA-level variables in both the capital flows and returns equations to control for any relationship that may exist because of their mutual association with such variables.

Even if capital flows to a sector or market can be successfully purged of changes in investor sentiment (i.e., they are exogenous with respect to returns), capital inflows or outflows may affect valuations if the sector is segmented from other asset classes (Gompers and Lerner, 2000). If segmentation exists, exogenous increases in capital flows may put upward pressure on asset prices and returns. For example, an increase in the target allocations of pension funds to commercial real estate may result in greater competition for existing properties and rising prices. This "price pressure" will likely be greatest when pension funds and other investors are aggressively growing their real estate portfolios. Moreover, the lead time required to bring additional commercial properties to the market is likely to be significantly longer than the time required to increase the supply of venture capital firms or other financial assets. This inelastic supply of available real estate investments in a given local market, coupled with the geographical segmentation that characterizes commercial real estate markets should, in theory, produce a greater likelihood of price pressure in response to exogenous shifts in demand than would be observed in the private equity market studied by Gompers and Lerner (2000). In fact, private real estate markets provide a particularly interesting test case for the analysis of the impacts of capital flows on returns.

Data and Descriptive Statistics

NCREIF is a not-for-profit institutional real estate industry association. Established in 1982, NCREIF serves the real estate investment industry by collecting, processing, validating and then disseminating information on the risk/return characteristics of commercial real estate assets owned by institutional—primarily pension fund—investors. NCREIF's flagship index, the NCREIF Property Index (NPI), tracks the quarterly total return performance of a large pool of individual commercial real estate properties acquired in the private market for investment purposes only.[5]

[5] Detailed information on NCREIF and the NPI is available at www.ncreif.com

To be included in the NPI, the asset must be an existing property, be at least 60% leased if within one year of completion of development, and be wholly owned or in a joint venture structure. If in a joint venture, the data is reported so that the returns can still be calculated on the entire property – not just the joint venture interest. Although there are levered properties in the NPI, investment performance is reported on an unlevered basis. The property composition of the NPI changes quarterly as data contributing NCREIF members buy and sell properties. However, all historical data remain in the database and in the Index.

The NPI is compiled from the quarterly returns of individual properties before the deduction of portfolio-level management fees, but inclusive of property level management fees. Each property's quarterly return is weighted by its market value relative to the total market value of the properties that comprise the NPI Index. In addition to total returns, the income and capital gain components of the total return are separately reported.

Although the NPI Index is available beginning in the first quarter of 1978, the limited number of data contributing members and constituent properties in the early years of the NPI does not support CBSA and sub-CBSA-level analyses. Therefore, to minimize noise in the construction of our NPI return series, we begin our sample period in the third quarter of 1983. To further ensure an adequate number of properties are included in the calculation of our CBSA-level indices, we imposed the condition that the average number of constituent properties over the 1983:3 to 2005:2 sample period must be equal to or greater than ten and that there must be at least four properties in the NPI Index in any quarter. These screens reduced the number of usable CBSAs to 43. We also had sufficient CBSA-level data to construct apartment returns for ten different CBSAs. The corresponding number of CBSAs for our retail, office, and industrial analyses are 12, 20, and 28, respectively.

Each quarter, the market value of properties in the NPI changes for several reasons including: (1) capital appreciation, (2) net capital flows from NCREIF member acquisitions and dispositions, and (3) properties added to the database from new members. We remove the effects of (1) and (3) from the net change in market value to capture the change in market value due to a flow of funds into the CBSA from net acquisitions. This "raw" capital flow variable is defined as *FLOWS* and is constructed for the U.S. as a whole, for each of our 43 CBSAs, and for each of our sub-CBSA property type indices.[6]

Since we investigate the dynamic behavior of institutional capital flows and returns, it is important to consider the appropriate measure of fund flows in our regressions. Froot, O'Connell and Seasholes (2001) and Ling and Naranjo (2003, 2006) argue that the impact of capital flows on returns is likely to be conditional on the size of the market. Based on this argument, we create an additional flow variable, *RFLOWS*, for use in our regressions that is defined raw capital flows divided by the corresponding total market value of NPI properties in that CBSA at the beginning of the quarter.

To more broadly control for other potential sources of variation in our quarterly returns and flows equations, we also include lagged values of the three Fama-French risk factors: *MKT*, *SMB*, and *HML*. *MKT* is the total return on the value-weighted market portfolio, as measured by the Center for Research in Securities Pricing (CRSP), minus the corresponding return on U.S. Treasury securities from CRSP. *SMB* is defined as the total return on a portfolio of small cap stocks in excess of the return on a portfolio of large cap stocks. Finally, *HML* is the total return

[6] We did not include capital expenditures as capital flows under the assumption that CAPX are intended to preserve the existing capital investment.

on stocks with high ratios of book-to-market value in excess of the returns on a portfolio of stocks with low book-to-market ratios.[7]

The majority of the total return typically earned by commercial real estate investors is provided by current income not capital gains. Thus, commercial real estate assets can generally be characterized as "value" assets with high book-to-market-value ratios. We therefore posit a positive relation between *HML* and NPI returns; that is, as stock investors rotate out of "growth" stocks (with low book-to-market-value ratios) into value assets, we expect the private commercial real estate sector to benefit from this capital rotation.

The use of the NPI income return as an explanatory variable in our analysis is motivated by the work of Bekaert and Harvey (2002), who argue that, in a rational pricing model, current (dividend) yields will be decreasing in the growth rate of dividends and increasing in the discount rate. Therefore, dividend yields may be useful in capturing permanent price effects induced by a change in a sector's cost of capital. To control for long-term interest rate levels and trends, we also include the lagged quarterly yield on constant maturity 10-year Treasury securities.

Descriptive statistics from the aggregate U.S. dataset are presented in Table 1. The mean and standard deviation of our quarterly data are presented in the first two columns followed by minimum and maximum values for each variable.

The market value of the aggregate NPI averaged $59.2 billion (in 2005:2 dollars) over the 1983:3 to 2005:2 time period, with a standard deviation of $41.6 billion. The NPI market

[7] Fama and French (1996) show that the cross-sectional variation in expected stock returns can be explained by their three factor model. They argue that *SMB* and *HML* are state variables in an intertemporal asset pricing model, although rational asset pricing theories do not clearly show how *SMB* and *HML* are related to the underlying undiversifiable macroeconomic risks. However, there is some recent empirical and theoretical work that links the Fama-French factors to undiversifiable macroeconomic risks (Liew and Vassalou, 2000, and Lettau and Ludvigson, 2001). The quarterly Fama-French risk factors were obtained from Ken French's website.

value ranged from a low of \$8.6 billion in 1983:3 to a high of \$165.9 billion in 2005:2. This increase in aggregate market value over the sample period was largely driven by an increase in constituent properties and contributing members.

Aggregate quarterly NPI returns, *RET*, averaged 2.03 percent over the sample period, ranging from a low of -5.33 percent (1991:4) to a high of 5.34 percent (2005:2). The standard deviation of *RET* is 1.60 percent. The income component of the total return, *INCRET*, averaged 1.92 percent per quarter, or 94 percent of the average total return. With a standard deviation of just 0.19 percent, however, the income component has exhibited significantly less volatility than the total return.

Aggregate NPI flows (*FLOWS*) for all NCREIF markets averaged \$1.5 billion a quarter and ranged from a low of -\$2.3 billion (1997:3) to a high of \$14.1 billion (2005:1) over the study period. The standard deviation of the inflation-adjusted NPI flows was \$2.5 billion. *RFLOWS* averaged 3.09 percent per quarter and have displayed substantial volatility, ranging from a low of -4.77 percent to a high of 10.65 percent over the study period. Given the relatively small average magnitude of *RFLOWS*, it would seem unlikely that capital flows into, and out of, NCREIF owned properties would have a significant effect on NPI property values and returns. Instead, we expect the signaling of changes in investor sentiment imbedded in NPI flows may be more important than the "price pressure" impact of these flows.

The stock market risk premium (*MKT*) has averaged 1.96 percent per quarter, but has displayed significant volatility, ranging from a low of -24.32 percent to a high of 20.65 percent. *SMB* and *HML* have averaged 0.26 percent and 0.97 percent, respectively, and have also displayed substantial volatility over the sample period. The constant maturity yield on 10-year Treasury securities averaged 7.01 percent over the sample period.

Panel A of Table 2 contains the contemporaneous correlations among the variables used in our analysis. The first column in Panel A reveals that aggregate NPI total returns (*RET*) are positively correlated (ρ=0.193) with inflation-adjusted aggregate NPI flows (*FLOWS*). However, *RET* displays no significant contemporaneous correlation (ρ=0.018) with relative NPI flows. Prior empirical studies suggest that commercial real estate returns are likely to be positively correlated with the contemporaneous premiums earned by value stocks. The positive monthly correlation of *RET* with *HML* (ρ=0.085) provides some support for this relation. However, *RET* is negatively correlated with *MKT* (ρ=-0.047) and *SMB* (ρ=-0.142). The correlation between *RET* and 10-year Treasury yields and *MKT* cannot be distinguished from zero.

The second column in Panel A of Table 2 reveals that aggregate NPI flows are highly correlated with our constructed measure of relative fund flows (ρ=0.579). NPI capital flows also display positive contemporaneous correlations with *SMB* and *HML*, but are significantly negatively correlated with *TRYLD* (ρ=-0.440). The correlations between *RFLOWS* and the three Fama-French risk variables are largely consistent with the *FLOWS* correlations.

Panel B of Table 2 documents evidence of simple univariate relations between the lead and lagged values of our two endogenous regression variables, NPI returns and flows. Aggregate NPI returns are highly correlated with returns in both prior and subsequent quarters. The high degree of autocorrelation is generally attributable, at least in part, to the temporal lag bias (i.e., "smoothing") associated with NCREIF returns, which we control for in our conditional analysis. In sharp contrast, *RFLOWS* displays only moderate correlation with *RFLOWS* in the prior or subsequent quarters (ρ=0.093). Thus, the strong autocorrelation observed in raw NPI returns is not observed in NPI capital flows. Moreover, the correlation between $RFLOWS_{t-1}$ and $RFLOWS_{t+1}$ is negative (ρ=-0.108), suggesting that the moderate positive correlation between $FLOWS_{t-1}$ and $FLOWS_t$ is reversed in the subsequent quarter.

What about the lead-lag relation between NPI capital flows and returns? In Figure 1, we graph *RET* and *RFLOWS* over the sample period. Relative capital flows are measured on the left vertical axis, NPI total returns on the right. Inspection of Figure 1 reveals little evidence of a consistent univariate relation between capital flows and returns over the full sample period. This impression is largely confirmed by the correlations reported in Panel B of Table 2. Current quarter NPI returns are not significantly correlated with either contemporaneous relative flows (ρ=0.018) or lagged flows (ρ=0.027). However, returns in quarter *t*-1 are positively associated with flows in quarters *t*+1 (ρ=0.164), suggesting a two quarter lag between returns and subsequent flows. Similarly, *RFLOWS* in quarter *t*-1 are positively associate with returns in quarter *t*+1 (ρ=0.089).

Although the aggregate return and capital flow data are interesting, the focus of our analysis is on the relation between NPI capital flows and returns disaggregated to the CBSA level. Table 3 provides mean values of selected variables for each of our 43 CBSAs, aggregated across all property types, as well as the mean, standard deviation, and range of the CBSA mean values. The mean market value of NPI properties in our 43 CBSA sample (in 2005:2 dollars) averaged $1,145 million over the 1983:3 – 2005:2 sample period, with a low of $189 million in Camden, New Jersey and a high of $4,311 million in Los Angeles. The corresponding mean number of properties constituting the NPI averaged 44 across the 43 CBSAs, ranging from a minimum of 13 in Camden to a high of 144 in Chicago.

Mean NPI income returns averaged 2.04 percent across the 43 markets with a standard deviation of just 0.11 percent. In fact, mean quarterly income returns ranged from a low of 1.84 percent to a high of just 2.29 percent. This 45 basis point range in average quarterly income returns reveals that the average income return (dividend yield) on core institutional properties varied little across CBSAs over our 20-plus year sample period. Mean NPI total returns (*RET*) averaged 2.13 percent across the 43 markets with a standard deviation of just 0.38 percent. The remarkably small 9 basis point differential between mean income and mean total returns is dramatic evidence of the extent to which total returns on investments in core institutional properties are driven by the income component. Nominal quarterly capital flows averaged $36.6 million and ranged from a mean of $2.4 million in Milwaukee to a mean of $127.6 in Los Angeles. *RFLOWS* averaged 4.4 percent across the 43 CBSAs. We also obtained CBSA-level information on population, non-agricultural employment, per capita income, and single- and multifamily housing starts from Economy.com to control for time series variation in local market conditions in our VARs.

Research Methodology

Simultaneous vector autoregressive (VAR) methods have proven successful for forecasting systems of interrelated time series variables (see Sims, 1980). We employ VAR models to examine the relationships among institutional investor real estate capital flows and property returns.

More specifically, we seek to answer two questions. First, do NPI capital flows predict NPI returns over and above the predictions of lagged returns? Second, do NPI returns predict flows over and above the predictions of lagged flows? Our VAR models also include several national level control variables, such as stock returns and interest rates, as well as several CBSA-level variables, such as employment, income per capital, and housing starts. By separately examining the CBSAs, we are able to disentangle the influence of location on the conditional dynamics of institutional capital flows and returns.

In its simplest form, a VAR model is composed of a system of regressions where a set of dependent variables are expressed as linear functions of their own and each other's lagged values, and possibly some other exogenous variables. In more technical terms, a vector autoregression model is the unconstrained reduced form of a dynamic simultaneous equations model.

In general terms, an unrestricted pth-order Gaussian VAR model can be represented as:

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_k Y_{t-p} + e_t,$$

where Y_t is a vector of variables, μ is a p x 1 vector of intercepts, Φ_1, Φ_2, …, Φ_k are p x p matrices of parameters with all eigenvalues of Φ having moduli less than one so that the VAR is stationary, and e_t is a vector of uncorrelated structural shocks [~ $NID(0,\Omega)$]. In a bivariate framework of only flows and returns, the diagnol coefficients of Φ represent conditional momentum in flows and returns, while the off-diagnol coefficients of Φ represent conditional positive feedback trading (flows following returns) and conditional anticipation effects (returns following flows). The off-diagnol elements of Ω capture the price-impact effect of flows on returns.

We first estimate the above unconstrained VAR system at the aggregate U.S. level and then for each of our 43 CBSAs over the 1983:3-2005:2 quarterly sample period using data aggregated across all property types. We then estimate property specific equations at the CBSA-level in those CBSAs with adequate data for the apartment, retail, office, and industrial property types.

We obtain maximum likelihood estimates of Φ and Ω using iterated least squares. The lag-length of the VAR is chosen by looking at the AIC and the likelihood ratio for various choices of p. We find that four lags provide the best fit. It is important to note that the lagged returns in the return equation control for the well-documented autoregressive nature of NCREIF returns (i.e., the smoothing bias). Thus, the reported flow coefficient estimates s are marginal effects. For the aggregate results, we also use the estimates of Φ to form impulse response functions, which provide the time path of the short-run dynamic relationships from a shock to the variables in the system. In particular, we compute generalized impulse responses from a one standard deviation flow shock and examine the effects on flows and returns. We then compute impulse responses from a one standard deviation total return shock and examine the effects on flows and returns.

Vector Autoregressive Results

Aggregate Results

In this section, we examine the conditional covariation results using return and flow data aggregated across the 43 CBSAs and four property types. We estimate three unrestricted VAR models: a bivariate model, a seven-factor model, and an eleven-factor model. The bivariate model consists of total NPI capital flows and aggregate NPI returns. Next, using our seven-factor model, we seek to determine whether the relations we uncover in our bivariate model exist after controlling for lagged interest rate levels, lagged income returns, and the lagged Fama-French risk factors (*MKT, SMB*, and *HML*). Finally, we estimate an augmented version of the seven-factor model that also includes the following demographic/market variables: change in the number of multifamily housing starts in the U.S. over the prior four quarters (*MULTI*); change in the number of single-family housing starts over the prior four quarters (*SINGLE*); change in non-agricultural employment of the prior four quarters (*EMPLOY*); and change in per-capita income over the prior four quarters (*INCOME*). The results from these three models provide conditional evidence on the influence of NCREIF returns on fund flows, and vice versa, as well as the dynamics of the relationship.

The first two columns in Table 4 contain the results for the bivariate model. Turning first to the bivariate return (*RET*) equations, we find that aggregate NPI returns are influenced by returns in previous quarters. Given the widely documented autocorrelation in NPI return series, this result was expected. Although not reported, the sum of the four lagged coefficients on *RET* is 0.926 with a p-value of 0.000, indicating a strong relation between contemporaneous and lagged returns over the prior four quarters. Controlling for the autoregressive nature of NCREIF returns (the smoothing bias), we find that lagged capital flows have no impact on current returns; in fact, even the sum of the flow coefficients over the prior four quarters is not statistically significant (p-value=0.24) in the return equations. Thus, in the absence of additional control variables, capital flows are not predictive of future returns. Overall, the simple bivariate model is able to explain 62 percent of the variation in current NPI returns.

In column three of Table 4, we add controls for lagged interest rate levels (*TRYLD*), the income return on the aggregate NPI in the prior quarter (*INCRET*), and the three Fama-French risk factors (*MKT*, *SMB*, and *HML*). Similar to our bivariate results, we find a strong relation between RET_t and returns in quarters *t*-1, *t*-2, and *t*-4. The sum of the four lagged coefficients on *RET* is 0.878 with a p-value of 0.000. Unlike our bivariate results, however, we now find evidence that lagged flows in quarter *t*-2 and *t*-3 positively impact current returns. Moreover, the sum of the lagged flow coefficients is 0.15 with a p-value of 0.024, indicating that the cumulative effect of lagged flows on returns is positive and significant. Although the coefficient on *INCRET* is positive and significant, the estimated coefficients on *MKT*, *SMB*, *HML,* and *TRYLD* cannot be distinguished from zero. The adjusted R-squared for the seven-factor *RET* model is 0.652.

Finally, in column five of Table 4, we report the results of estimating the aggregate *RET* equation augmented further with the additional demographic/market variables: *MULTI, SINGLE, EMPLOY,* and *INCOME.* Including these additional variables in the estimation increases the adjusted R-squared to 0.777 and produces some interesting results. First, the estimated coefficients on *MULTI, EMPLOY,* and *INCOME* are all positive and statistically significant. However, the addition of these four variables causes the coefficient on *INCRET* to become insignificant. In addition, the strong positive relation between *RET* and returns in quarter *t*-1 and *t*-2 found in the first two specifications no longer exists. Interestingly, the explanatory power of RET_{t-4} actually increases (coefficient of 0.551, t-statistic of 6.012). The sum of the lagged coefficients on *RFLOWS* is 0.193 with an associated p-value of 0.004. Thus, lagged capital flows also continue to play a significant role in explaining the variation in current returns.

In summary, we find that both lagged returns and lagged flows influence current returns at the national level. This result is consistent with the widely held belief among practitioners that that capital flows in private real estate markets are predictive of subsequent returns.

We now turn to the capital flow equations that were estimated simultaneously with the return equations. In our bivariate model, *RFLOWS* displays no relation to lagged returns. That is, NCREIF investors do not appear to chase returns—at least at the aggregate level. Moreover, *RFLOWS* is not associated with flows over the prior three quarters, although the coefficient on

RFLOWS$_{t\text{-}4}$ is positive and significant at the 10 percent level. The adjusted R-squared of the bivariate estimation of the flows equation is just 0.012.

When *INCRET*, *MKT, SMB*, and *HML* are added to the *RFLOWS* equation (column 4), none of the lagged flow (or return) variables are statistically significant. However, current NPI flows are weakly positively associated with *MKT* and *HML*. Although the coefficients on *MULTI, EMPLOY,* and *INCOME* are all positive and statistically significant in the *RET* equation, these variable do not play a statistically significant role in explaining the time series variation in *RFLOWS* (column 6). Overall, the eleven-factor *RFLOWS* model is able to explain only 1.4 percent of the variation in current flows. Clearly, the prediction of institutional capital flows is difficult at the aggregate level.

In Figure 2, we plot the impulse responses of a generalized one standard deviation innovation in NCREIF flows and returns on both flows and returns. As described in Pesaran and Shin (1998), generalized impulses do not depend on the VAR ordering. However, as a robustness check, we also examined various Cholesky orderings and obtained similar results. The impulse responses are based on the eleven-factor VAR model estimates. The top left graph, which depicts the response of quarterly returns to a one standard deviation return shock, suggests a significant role for lagged returns in explaining contemporaneous returns. The return shock produces an initial positive return response that quickly dissipates, but is followed by another positive spike four quarters later. The top right graph depicts the response of returns to a shock in flows. This shock produces a slight increase in returns in the subsequent two or three quarters that largely dissipates thereafter. A shock in aggregate NCREIF returns does not have a measurable impact on NCREIF flows (bottom left panel). Finally, looking at the bottom right graph, we see that an innovation in aggregate flows results in a temporary increase in subsequent flows, which then quickly dissipates toward zero.

Results Disaggregated by CBSA

As reported above, we find strong conditional evidence using aggregate level data that both lagged returns and lagged capital flows influence current returns to U.S. institutional investors. However, these aggregate results may be masking significant cross-sectional differences across metropolitan areas and property types. To address this issue, we separately estimate our eleven-factor VAR for the forty-three CBSAs in our sample. In Table 5 we report the *percentage* of CBSA regressions in which a particular coefficient is significant--either positively or negatively--at the 10 percent level or greater.

The first two rows in the top panel of Table 5 contain our results for the return equations corresponding to the percentage of statistically significant positive or negative coefficients. For example, the estimated coefficient on RET_{t-1} is positive and significant in 19 percent of the CBSA return equations. In none of the return equations was the estimated coefficient on RET_{t-1} negative and significant. NPI returns are also strongly positively influenced by returns in quarter t-2, t-3, and t-4. In fact, the estimated coefficient on RET_{t-4} was positive and significant in 53 percent of the “All Property Types” return regressions. The sum of the estimated coefficients on lagged returns is statistically significant in 91 percent of the CBSA regressions, which is expected given the autoregressive nature of NCREIF returns.

The aggregate regressions reported in Table 4 indicate that a significant role is played by lagged capital flows in explaining the variation in the aggregate NPI return index over time. However, the results reported in Table 5 suggest that this aggregate result was driven by a limited number of the forty-three CBSAs. More specifically, the estimated coefficients on the four lagged values of *RFLOWS* are positive and significant in just 9 percent, 12 percent, 14 percent, and 7 percent, respectively, of the 43 return regressions. In fact, the estimated coefficient on $RFLOWS_{t-1}$ is almost half as likely to be negative as positive. Looking at the cumulative four quarter effect of flows on returns, we find returns in that 23 percent of the CBSAs are influenced by flows. Taken together, these results show that there is a great deal of variation across CBSAs in the impact of NPI capital flows on subsequent returns.

What about the influence of our other control variables on NPI returns? The estimated coefficients on *INCRET*, *MKT*, and *SMB* are positive and statistically significant in less than 10 percent of the return regressions. The estimated coefficients on *MULTI* and *SINGLE* are significant in 16 percent and 12 percent, respectively, of the return equations. The estimated coefficient on *TRYLD* is negative and significant in 70 percent of the return regressions, suggesting that CBSA-level returns are strongly inversely related to the level of lagged interest rates. Finally, the coefficients on *EMPLOY* and *INCOME* are positive and significant in 44 percent and 26 percent, respectively, of the return regressions, indicating a prominent role for changes in employment and per-capita income in explaining NPI returns. Nevertheless, it is clear that the influence of our control variables is far from consistent across metropolitan areas. This suggests that models intended to predict private market returns must be estimated using data disaggregated to, at least, the metropolitan level.

Corresponding results for the CBSA-level flow equations aggregated across all property types are reported immediately below the *RET* results in the top panel of Table 5. In general, our model variables are statistically significant in a very limited number of the *RFLOWS* equations, although the sum of the four lagged flow coefficients is significant in 28 percent of the CBSA-level estimates. Overall, the CBSA-level flow results suggest that the prediction of CBSA-level NCREIF capital flows is a difficult task.

Results Disaggregated by Property Types at the CBSA-level

The results reported in the top panel of Table 5 are disaggregated by CBSA, but aggregated across all property types. It is possible that our CBSA-level results may be masking significant variation by property type within a given metropolitan area. To examine this possibility, we separately estimate the eleven factor VAR specification by major property type in all cases where sufficient NCREIF data are available. More specifically, we were able to identify 10 CBSAs with sufficient data to estimate our dynamic VAR model for apartments. Similarly, we identified 12, 20, and 28 CBSAs, respectively, with adequate data for estimation of separate retail, office, and industrial models.[8]

For all four property types, lagged returns play a significant role in explaining current NPI returns. This result, however, is most pronounced for retail properties, where the accumulated return coefficients over the prior year are significant in 100 percent of the CBSA regressions. It is worth noting that RET_{t-4} is consistently the most significant of the lagged returns, a somewhat surprising result. The absence of a significant role for lagged capital flows in explaining current returns is also evident in the property level *RET* equations. Clearly, the lack of explanatory power displayed by NPI capital flows in the CBSA-level regressions is robust with respect to disaggregation by property type.

[8] Recall that the data screens require that the average number of constituent properties over the 1983:3 to 2005:2 sample period must be equal to or greater than ten and that there must be at least four properties in the NPI Index in any quarter). The remainder of Table 5 contains these property-level results.

Several other property level results are worth noting. First, the lagged NPI income return (*INCRET*) is not significant in any of the retail return regressions. It is, however, significant in 10 to 20 percent of the regressions for the other three property types. *MKT* has a significant negative effect on NPI returns in 10 percent of the apartment regressions, but is positive and significant in 20 percent of the office return regressions. The significance of *EMPLOY* in the "All Property Types" regressions is clearly driven by the importance of this variable in the office return regressions, where it is positive and significant in 50 percent of the regressions. This compares with 8 percent in the retail regressions and 20 percent in the apartment regressions. Conversely, *INCOME* is clearly more important in the apartment return regressions than in the retail office, and industrial equations. Overall, the property level regressions provide evidence of significant variation across property types in the dynamic relation between capital flows and returns.

Some Additional Robustness Checks

We performed various additional robustness checks on the conditional relation between NPI flows and returns. In particular, we examined the stationarity of the variables, time variation of our results, the influence of public real estate market returns, the measurement of flows relative to the flows across all of the markets (instead of relative to flows within a market), inflation-adjusted flows, and potential asymmetric and nonlinear effects. Though not tabulated, we describe below the results corresponding to the various robustness checks.

First, to insure we are using the appropriate dynamic model, we examined whether the flow and return time series variables are stationary; non-stationarity would require the use of a vector error-correction (VEC) model.[9] Unit root tests indicated that the various series were stationary.

To assess the robustness of our results with respect to time, we separated the analysis into two non-overlapping sub-periods, 1983-1993 and 1994-2005, as well as a 15-year sub-period from 1990-2005. Similar to the earlier reported results, we find little time variation in the influence of NPI flows on NPI returns and vice versa. In particular, over each of the sub-samples we find a very small decrease in the number of instances where returns influence returns, flows influence returns, and returns influence flows. The frequency of flows influencing flows remains constant over each of the sub-periods.

We also examined the potential influence of lagged real estate investment trust (REIT) returns on NPI returns and flows using our eleven factor model. REIT returns, as captured by the National Association of Real Estate Investment Trust (NAREIT) Equity Index, have an insignificant effect on both flows and returns. More specifically, in the aggregate specification the t-statistics on the NAREIT coefficients were insignificant (-0.05 and 1.11 in the return and flow equations, respectively). Moreover, including the NAREIT returns did not affect the earlier reported results and inferences corresponding to the other variables in the specification. At the disaggregated level, the inclusion of NAREIT returns also did not change our reported results.

As additional robustness checks, we also examined the effect of measuring flows relative to the NCREIF capital flows across all of the CBSA markets (instead of relative to flows within a single market). Measuring flows relative to the total across all NCREIF markets yields similar

[9] In general, a series is non-stationary if its mean, autocovariances, or other higher moments are time dependent. For example, if the mean of a series varies with respect to time, it is likely to be non-stationary. Simply stated, the test for a unit root (i.e., non-stationarity) in a time-series is the test that a regression of a series on itself lagged one period yields a coefficient of one. This test is complicated by several features arising from the non-stationarity of the series under the null hypothesis.

results to those reported above. For example, in Table 5 the summed effect of flows on returns is significant in 23% of the CBSAs, whereas it is significant in 20% of the CBSAs using the across market relative specification.

To test for nonlinearities in the relation between flows and returns, we included squared flows and squared returns in the eleven factor model. We find that the squared variables are significant in less than 8 of the 43 CBSAs, and their inclusion did not affect the significance of the other variables. To test for potential asymmetric effects, we also separately examined the influence of positive and negative flows (returns) and changes in relative flows greater than 5% (returns). The inclusion of these asymmetric variables also yields similar results to those reported. Additionally, the asymmetric flow and return effects on returns are significant in less than 5 of the CBSAs for each of the asymmetric variables, while they are significant in the flows specification for less than 10 of the CBSAs. Overall, the nonlinear and asymmetric effects are greater for the flows specification than the returns specification.

Summary and Conclusion

The importance of capital flows in asset pricing has received significant attention in public securities markets. However, real estate practitioners have long argued that the relation between capital flows and asset prices is more pronounced in private markets that generally lack the liquidity and supply elasticity of public securities markets. However, a rigorous analysis of the dynamics of capital flows and returns in private real estate markets has not yet been undertaken. This is a significant void in the literature given the size of the private commercial real estate market and given that the supply inelasticities inherent in commercial real estate markets should make asset prices and returns in these markets more susceptible to exogenous demand shocks in the form of capital flows.

This paper examines the short- and long-run dynamics among institutional capital flows and returns in private real estate markets. The main tool of analysis is a vector autoregressive (VAR) regression model in which both institutional capital flows and returns are specified as endogenous variables in a two equation simultaneous system. We also include other exogenous variables such as lagged interest rates, the Fama-French factors, building starts, and changes in employment and per capita income in an attempt to purge the capital flow and return equations of any relationship that may exist because of their mutual relation to these exogenous variables and risk factors.

We first estimate our VARs using capital flow and return data that are aggregated across all U.S. metropolitan areas and property types. However, because increases or decreases in capital flows may have different effects in different segments of the private real estate market, we next disaggregate our analysis by major metropolitan areas. In particular, we examine whether capital invested in 43 metropolitan areas by members of the National Council of Real Estate Investment Fiduciaries (NCREIF) is associated with higher, or lower, property returns and capital flows in subsequent periods. Simultaneously, we examine whether quarterly real estate returns in core business statistical areas (CBSAs), as measured by NCREIF, are predictive of future institutional returns and capital flows by NCREIF members in these CBSAs. As a further robustness check, we also examine the short- and long-run dynamics among CBSA-level capital flows and returns disaggregated by the four major property types: office, industrial, retail, and apartment.

When aggregating across CBSAs and property types, we find evidence that both lagged NCREIF returns and lagged NCREIF flows significantly influence current returns. However, these aggregate results mask significant cross-sectional variation across different metropolitan areas and property types. In particular, we demonstrate that our aggregate results are driven by a limited number of CBSAs. Thus, the impact of lagged flows and returns on current returns varies substantially across metropolitan areas. We find no evidence that returns are predictive of future NPI capital flows. We also document that institutional capital flows are not generally predictive of future capital flows. In summary, institutional investors do not appear to systematically chase returns or the capital flows of other institutional investors.

Clearly, additional work on the return-flow relation in private real estate markets is warranted. In particular, it would be interesting to test for a return-flow relationship using a measure of capital flows broader than the institutional capital flows measured in this paper with NCREIF data. Capital flow data available since 2002 from Real Capital Analytics may prove to be helpful in this effort.

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Figure 1: NCREIF Relative Capital Flows and Total Returns

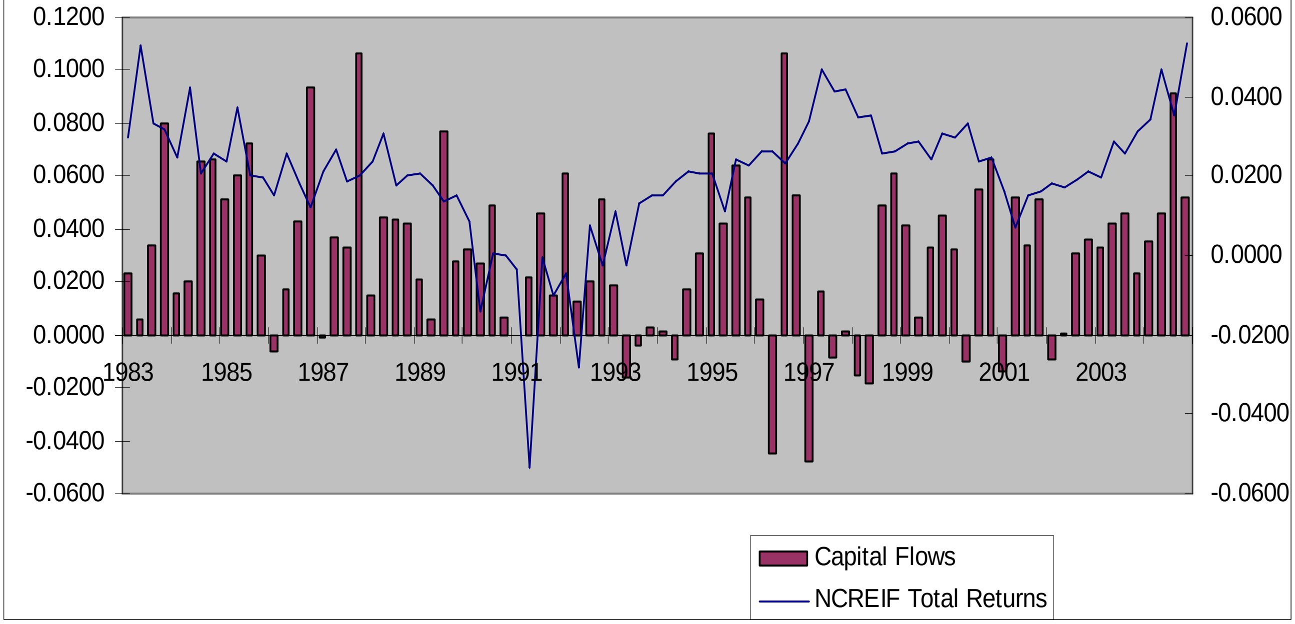

Figure 2
Aggregate NPI Returns and Flows: Impulse Responses from Vector Autoregressive Model (Eleven-Factor, 1983:03 -2005:2)

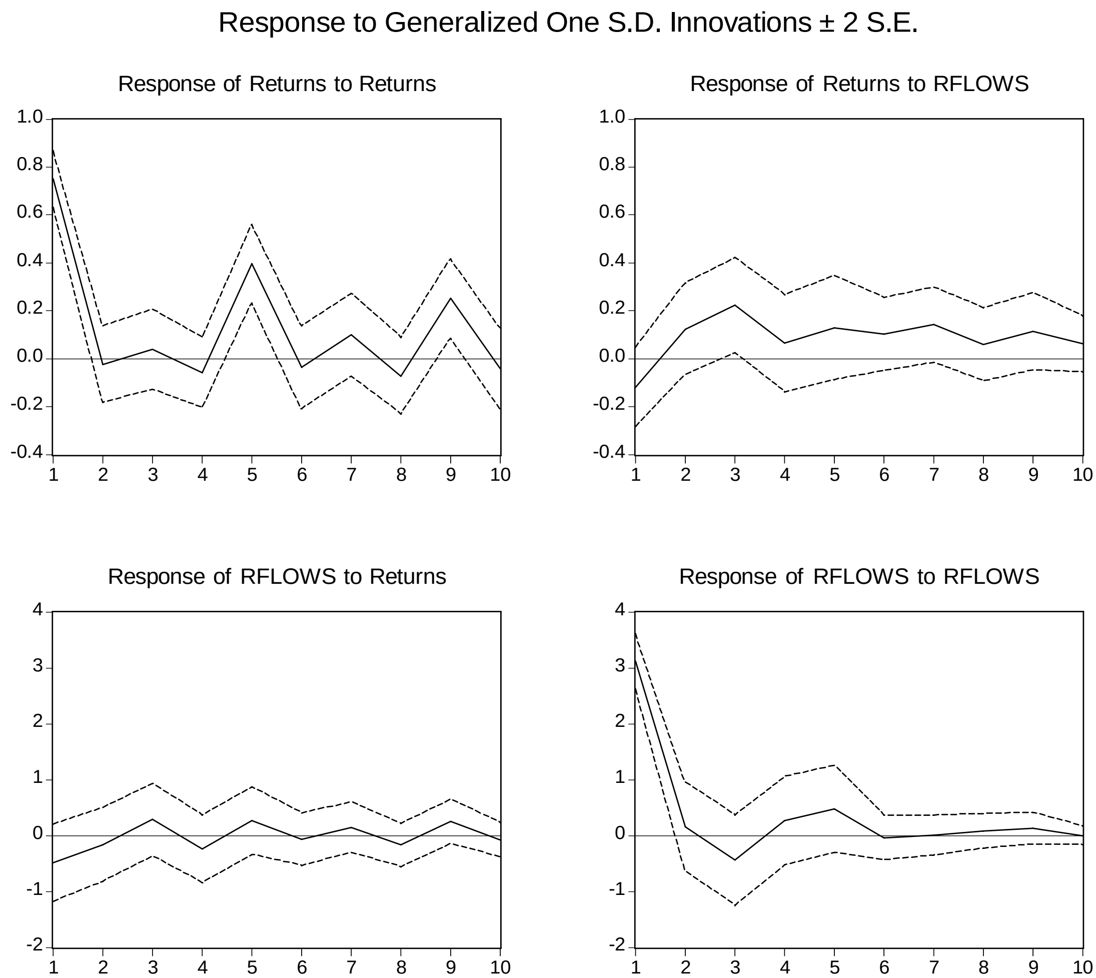

Table 1
Descriptive Statistics for Aggregate Variables: 1983:3 - 2005:2

Variables	Mean	Std. Dev.	Minimum	Maximum
NPIMV (in billions of 2005 $s)	59.2	41.6	8.6	165.9
NUMPROP	2,322	939	989	4,554
INCRET	1.92%	0.19%	1.56%	2.24%
RET	2.03%	1.60%	-5.33%	5.34%
FLOWS (in billions of 2005 $s)	1.5	2.5	-2.3	14.1
RFLOWS	3.09%	3.06%	-4.77%	10.65%
MKT	1.96	8.42	-24.32	20.65
SMB	0.26	5.35	-10.84	19.10
HML	0.97	6.91	-32.02	20.59
TRYLD	7.01	2.23	3.33	13.56

NPIMV : total market value of properties that constitute the NPI index.
NUMPROP : Number of properties that constitute the NPI Index.
INCRET : Income return on the NPI Index
RET : Total return on the NPI Index.
FLOWS : Market value of properties added to, or deleted from, the NPI Index.
RFLOWS : FLOWS divided by the market value of the NPI Index lagged one quarter.
MKT : Total return on CRSP's value-weighted market index minus the CRSP three-month U.S. Treasury return.
SMB : Fama-French small firm minus big firm return factor.
HML : Fama-French high book to market minus low book to market return factor.
TREASYLD : Constant maturity yield on 10-year Treasury securitiy.

Table 2
Correlations of Aggregate Variables

Panel A: Contemporaneous Correlations

	RET	*FLOWS*	*RFLOWS*	*MKT*	*SMB*	*HML*	*TRYLD*
RET	1.0000						
FLOWS	0.1932	1.0000					
RFLOWS	0.0181	0.5786	1.0000				
MKT	-0.0466	0.0218	0.0909	1.0000			
SMB	-0.1424	0.3049	0.1883	0.4368	1.0000		
HML	0.0849	0.1147	0.0472	-0.3987	-0.1296	1.0000	
TRYLD	-0.0048	-0.4401	0.1372	-0.0457	-0.1901	0.0371	1.0000

Panel B: Lead and Lag Correlations

	RET_{t-1}	RET	RET_{t+1}	$RFLOWS_{t-1}$	$RFLOWS$	$RFLOWS_{t+1}$
RET_{t-1}	1.0000					
RET	0.6863	1.0000				
RET_{t+1}	0.7160	0.6863	1.0000			
$RFLOWS_{t-1}$	0.0181	0.0266	0.0888	1.0000		
$RFLOWS$	0.0528	0.0181	0.0266	0.0934	1.0000	
$RFLOWS_{t+1}$	0.1639	0.0528	0.0181	-0.1075	0.0934	1.0000

RET : Total return on the NPI Index.
FLOWS : Market value of properties added to, or deleted from, the NPI Index.
RFLOWS : *FLOWS* divided by the market value of the NPI Index lagged one quarter.
MKT : Total return on CRSP's value-weighted market index minus the CRSP three-month U.S. Treasury return.
SMB : Fama-French small firm minus big firm return factor.
HML : Fama-French high book to market minus low book to market return factor.
TRYLD : Constant maturity yield on 10-year Treasury security.

Table 3
CBSA-level Descriptive Statistics: Mean Values (1983:3 - 2005:2)

	Market Value NCREIF Prop (in $mil.) *NPIMP*	No. of Prop. *NUMPROP*	NCREIF Quartrly Inc. Return *INCRET*	NCREIF Quartrly Total Return *RET*	Net Capital Flows (in $mil.) *FLOWS*	Cap Flow as a % of Lagged NCREIF Val *RFLOWS*	Non-Ag. Employ (in thous)	% Chg Employ Last 4 qtrs *EMPLOY*	Income Per Capita (in $thous.)	% Change in Inc. Last 4 qtrs *INCOME*	Multi-Family Starts *MULTI*	Single-Family Starts *SINGLE*
Atlanta	2,055.4	107	2.05%	2.11%	82.1	4.0%	1,835.5	3.1	24.7	5.0	10,306	40,758
Austin	614.0	33	2.01%	1.64%	24.3	7.3%	501.1	4.4	22.9	5.1	4,497	8,374
Baltimore	835.9	37	2.15%	2.79%	28.5	3.2%	1,147.8	1.4	25.9	5.1	2,322	11,815
Bethesda	686.0	30	1.98%	2.33%	26.8	3.5%	477.7	2.3	35.7	5.0	1,416	6,012
Boston	1,189.0	22	2.10%	2.37%	58.9	8.6%	1,008.4	0.8	29.9	5.8	1,584	3,166
Cambridge	755.9	27	2.21%	2.44%	35.0	5.7%	767.5	0.8	33.1	5.9	955	2,818
Camden	189.2	13	1.96%	2.52%	3.6	3.0%	456.9	1.8	24.3	4.9	570	4,684
Charlotte	514.7	23	2.11%	2.29%	17.1	5.6%	620.5	3.1	24.1	5.4	3,446	11,509
Chicago	3,922.0	144	1.98%	1.99%	125.3	3.0%	3,544.0	1.2	26.5	4.6	7,402	22,200
Cincinnati	571.9	24	2.17%	1.79%	11.1	3.1%	900.6	1.9	23.5	5.1	2,443	9,016
Columbus	445.4	22	2.26%	2.11%	13.8	7.3%	782.3	2.2	23.5	5.1	3,522	8,175
Dallas	2,205.3	122	1.99%	1.39%	71.3	3.0%	1,601.8	2.4	26.6	4.5	9,614	20,406
Denver	1,351.0	61	1.96%	1.52%	37.9	3.2%	986.4	2.0	27.5	4.9	4,746	12,317
Ft. Lauderdale	696.3	34	1.95%	2.15%	22.7	7.9%	568.0	3.1	25.3	4.0	4,851	7,476
Fort Worth	321.6	20	2.14%	2.09%	7.8	3.2%	651.9	2.7	22.5	4.3	3,577	9,744
Houston	1,564.8	69	1.85%	1.08%	51.2	3.5%	1,925.8	1.6	24.9	4.5	7,040	22,189
Indianapolis	554.0	23	2.15%	1.64%	15.3	4.5%	727.2	2.6	24.2	5.1	2,339	9,831
Kansas City	410.5	22	2.15%	2.00%	11.7	3.5%	874.5	1.7	24.1	4.8	3,015	9,602
Los Angeles	4,311.1	132	2.00%	2.53%	127.6	3.3%	3,916.6	0.6	24.0	4.2	13,426	10,645
Memphis	372.8	25	2.29%	1.98%	11.9	3.9%	530.7	2.5	22.2	5.3	1,608	7,132
Miami	974.5	21	1.90%	1.85%	29.6	4.0%	899.1	2.2	20.8	4.1	5,937	6,905
Milwaukee	283.3	15	2.09%	1.63%	2.4	3.5%	778.1	1.3	25.2	4.8	2,212	3,751
Minneapolis	1,112.7	64	2.10%	1.86%	33.9	3.2%	1,496.8	2.2	27.7	5.1	4,454	16,681
Nashville	269.6	15	2.02%	2.21%	6.4	3.7%	587.7	2.8	23.4	5.4	2,861	9,061
New York	3,206.3	35	1.95%	2.34%	110.0	3.0%	4,911.1	0.4	29.7	5.1	11,061	5,298
Oakland	1,399.6	55	1.98%	2.49%	50.9	4.2%	906.0	1.9	29.2	4.9	3,258	7,338
Orlando	651.3	32	2.03%	2.17%	21.0	4.6%	696.2	5.2	21.1	4.5	6,302	15,919
Philadelphia	877.3	30	2.07%	2.44%	20.7	4.8%	1,761.7	0.9	27.0	5.2	1,778	9,408
Phoenix	1,414.5	72	1.94%	1.83%	44.9	4.0%	1,217.3	4.5	21.9	4.5	9,339	29,319
Portland	605.3	33	1.89%	1.87%	13.7	4.1%	796.6	2.7	24.0	4.7	4,272	9,247
Sacramento	439.4	20	2.05%	2.39%	10.2	7.3%	664.7	3.3	23.3	4.6	3,213	12,044
St. Louis	492.5	34	2.14%	2.13%	10.0	2.9%	1,219.6	1.4	24.2	4.7	2,516	11,273
Salt Lake	252.8	15	2.17%	2.04%	4.9	3.4%	452.7	3.0	21.3	4.6	1,619	4,779
San Antonio	269.7	16	1.99%	1.63%	7.9	5.4%	625.6	2.4	20.0	4.7	2,604	7,074

Table 3 continued
CBSA-level Descriptive Statistics: Mean Values (1983:3 - 2005:2)

	Market Value NCREIF Prop (in $mil.) *NPIMP*	No. of Prop. *NUMPROP*	NCREIF Annualized Inc. Return *INCRET*	NCREIF Annualized Total Return *RET*	Net Capital Flows (in $mil.) *FLOWS*	Cap Flow as a % of Lagged NCREIF Val *RFLOWS*	Non-Ag. Employ (in thous)	% Chg Employ Last 4 qtrs *EMPLOY*	Income Per Capita (in $thous.)	% Change in Inc. Last 4 qtrs *INCOME*	Multi-Family Starts *MULTI*	Single-Family Starts *SINGLE*
San Diego	1,519.1	47	2.04%	2.52%	58.3	6.2%	1,009.5	3.0	25.0	5.1	7,414	9,514
San Francisco	2,305.3	37	1.95%	2.62%	73.3	5.3%	951.3	0.4	39.1	5.5	2,104	1,533
San Jose	1,235.5	62	1.99%	2.65%	28.0	2.5%	853.6	1.2	33.0	5.3	2,879	3,231
Santa Ana	1,515.5	72	1.96%	2.58%	46.0	3.5%	1,204.9	2.5	28.8	4.7	5,329	7,231
Seattle	1,369.4	68	2.05%	2.49%	47.7	4.1%	1,143.1	2.7	29.5	5.3	7,304	9,691
Tampa	474.1	26	2.02%	2.01%	15.1	4.7%	982.9	3.5	22.1	4.7	6,350	14,711
Warren	223.0	16	2.27%	2.24%	7.6	4.4%	1,085.5	2.7	29.4	5.1	2,706	12,090
Wash. D.C.	4,260.6	94	2.01%	2.68%	127.5	5.3%	1,862.4	2.6	30.4	5.2	4,562	19,322
West Palm	501.8	23	1.84%	2.15%	21.0	5.3%	404.5	4.0	33.2	4.8	3,992	9,389
Mean	1,145	44	2.04%	2.13%	36.6	4.4%	1,171	2.3	26.2	4.9	4,482	10,992
Std. Dev.	1,061	33	0.11%	0.38%	34.4	1.5%	922	1.1	4.2	0.4	2,953	7,398
Minimum	189	13	1.84%	1.08%	2.4	2.5%	405	0.4	20.0	4.0	570	1,533
Maximum	4,311	144	2.29%	2.79%	127.6	8.6%	4,911	5.2	39.1	5.9	13,426	40,758

Table 4
Aggregate Vector Autoregressive Model Estimates: 1983:3-2005:2 (quarterly)

Variables	Bivariate Model		Seven-Factor Model		Eleven-Factor Model	
	RET	*RFLOWS*	*RET*	*RFLOWS*	*RET*	*RFLOWS*
Constant	-0.014	2.074**	-2.791*	9.646**	2.410	8.919
	(-0.056)	(2.683)	(-1.956)	(2.125)	(1.435)	(1.280)
RET_{t-1}	0.351**	-0.183	0.237**	-0.110	-0.004	-0.187
	(3.322)	(-0.562)	(2.208)	(-0.323)	(-0.042)	(-0.437)
RET_{t-2}	0.295**	0.284	0.302**	0.419	0.110	0.299
	(2.638)	(0.826)	(2.689)	(1.177)	(1.098)	(0.724)
RET_{t-3}	-0.103	-0.274	-0.064	-0.258	-0.062	-0.291
	(-0.908)	(-0.780)	(-0.570)	(-0.724)	(0.669)	(-0.757)
RET_{t-4}	0.382**	0.414	0.402**	0.336	0.550**	0.486
	(3.625)	(1.271)	(3.904)	(1.030)	(6.012)	(1.279)
$RFLOWS_{t-1}$	0.007	0.113	0.023	0.042	0.039	0.043
	(0.203)	(1.027)	(0.644)	(0.361)	(1.297)	(0.3429)
$RFLOWS_{t-2}$	0.039	-0.085	0.053*	-0.093	0.074**	-0.125
	(1.457)	(-1.026)	(1.934)	(-1.060)	(2.429)	(-0.993)
$RFLOWS_{t-3}$	0.019	0.003	0.046*	-0.015	0.016	0.087
	(0.700)	(0.041)	1.64	(-0.176)	(0.516)	(0.683)
$RFLOWS_{t-4}$	0.001	0.144*	0.027	0.098	0.063**	0.139
	(0.031)	(1.73)	(0.969)	(1.104)	(2.106)	(1.116)
INCRET			1.514**	-3.791*	-0.407	-3.384
			(2.327)	(-1.840)	(-0.594)	(-1.190)
MKT			0.015	0.080*	0.002	0.094*
			(1.065)	(1.721)	(0.210)	(1.778)
SMB			0.001	-0.010	0.017	-0.021
			(0.035)	(-0.136)	(0.867)	(-0.251)
HML			0.024	0.086*	0.025*	0.089
			(1.419)	(1.611)	(1.799)	(1.511)
TRYLD			-0.052	-0.048	-0.369**	-0.117
			(-0.925)	(-0.271)	(-4.546)	(-0.348)
MULTI					0.010**	-0.001
					(3.560)	(-0.076)
SINGLE					-0.007	-0.002
					(-0.922)	(-0.065)
EMPLOY					0.267**	0.072
					(2.369)	(0.153)
INCOME					0.137*	0.017
					(1.880)	(0.056)
Adj. R-squared	0.620	0.012	0.652	0.043	0.777	0.014

(t-statistics in parentheses: **,*; 5% and 10% significance levels, respectively)

Table 4 continued

We estimate the following unrestricted VAR model:

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_k Y_{t-p} + e_t,$$

where Y_t is a vector of variables, μ is a p x 1 vector of intercepts, Φ_1, Φ_2, …, Φ_k are p x p matrices of parameters with all eigenvalues of Φ having moduli less than one so that the VAR is stationary, and e_t is a vector of uncorrelated structural shocks [~ $NID(0,\Omega)$]. We obtain maximum likelihood parameter estimates using iterated least squares. The three models that we estimate are: a bivariate model, a seven-factor model, and an eleven-factor model. The bivariate model consists of total NPI capital flows and aggregate NPI returns. For the seven-factor model, we add 10-year CMT yields, NCREIF income returns, and the three Fama-French risk factors (*MKT, SMB*, and *HML*) to the bivariate model. For the eleven factor model, we estimate an augmented version of the seven-factor model that also includes the change in the number of multifamily housing starts in the U.S. over the prior four quarters (*MULTI*), change in the number of single-family housing starts over the prior four quarters (*SINGLE*), change in non-agricultural employment of the prior four quarters (*EMPLOY*), and the change in per-capita income over the prior four quarters (*INCOME*). The exogenous variables in the various VAR specifications are lagged.

Table 5

CBSA-level VAR Estimates: Percentage of CBSA Coefficients that are Significantly Positive or Negative at 10% Level or Higher

Endogenous Variables		RET_{t-1}	RET_{t-2}	RET_{t-3}	RET_{t-4}	Σ of Lagged *RET* Coef.	$RFLOWS_{t-1}$	$RFLOWS_{t-2}$	$RFLOWS_{t-3}$	$RFLOWS_{t-4}$	Σ of Lagged *RFLOWS*	*INCRET*	*MKT*	*SML*	*HML*	*TRYLD*	*MULTI*	*SINGLE*	*EMPLOY*	*INCOME*
All Property Types: 43 CBSAs																				
RET	+	19	28	12	53	91	9	12	14	7	23	9	7	9	14	0	16	12	44	26
	-	0	0	2	0		5	0	2	2		2	2	5	0	70	0	2	0	0
RFLOWS	+	7	5	5	9	7	2	2	0	2	28	9	12	5	19	9	5	5	5	14
	-	12	5	12	5		19	21	7	19		12	0	7	0	5	2	12	9	7
Apartments: 10 CBSAs																				
RET	+	20	20	0	50	70	10	0	20	10	0	10	0	20	10	0	10	0	20	20
	-	0	0	0	0		10	10	0	10		0	10	0	0	20	0	0	0	0
RFLOWS	+	0	0	10	10	10	0	0	0	10	0	0	0	10	0	20	0	0	0	0
	-	30	0	10	0		10	0	0	0		20	0	0	0	0	10	10	0	0
Retail: 12 CBSAs																				
RET	+	33	42	8	67	100	0	0	0	8	8	0	0	0	0	0	8	0	8	8
	-	0	0	0	0		0	8	8	0		0	8	0	0	33	0	0	0	0
RFLOWS	+	8	0	8	0	17	8	8	8	0	17	8	17	0	8	8	0	8	8	0
	-	8	0	0	0		17	8	0	17		17	0	17	8	0	8	0	0	0
Office: 20 CBSAs																				
RET	+	15	10	35	80	95	10	10	15	5	10	20	20	10	10	0	10	5	50	5
	-	0	0	0	0		0	5	0	0		0	0	0	0	30	5	0	0	5
RFLOWS	+	5	10	5	25	15	0	5	5	0	40	5	0	5	10	0	10	0	10	20
	-	5	5	15	5		5	15	15	20		5	0	0	0	5	0	10	10	5
Industrial: 28 CBSAs																				
RET	+	21	14	21	39	82	11	0	0	7	4	11	11	4	18	0	11	11	32	7
	-	4	0	0	4		0	0	0	0		0	0	7	0	25	0	4	0	4
RFLOWS	+	0	4	14	11	7	0	7	4	0	21	7	4	11	7	11	4	11	7	11
	-	7	4	0	0		18	14	7	7		7	7	0	0	11	4	4	10	0

Table 5 continued

We estimate an eleven-factor unrestricted VAR model for each CBSA over the 1983:3-2005:2 quarterly sample period:

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_k Y_{t-p} + e_t,$$

where Y_t is a vector of variables, μ is a *p* x 1 vector of intercepts, Φ_1, Φ_2, …, Φ_k are *p* x *p* matrices of parameters with all eigenvalues of Φ having moduli less than one so that the VAR is stationary, and e_t is a vector of uncorrelated structural shocks [~ $NID(0,\Omega)$]. We obtain maximum likelihood parameter estimates using iterated least squares. The eleven-factor model consists of CBSA-level NCREIF returns, relative flows, 10-year CMT yields, NCREIF income returns, the three Fama-French risk factors (*MKT, SMB*, and *HML*), the change in the number of multifamily housing starts in the U.S. over the prior four quarters (*MULTI*), change in the number of single-family housing starts over the prior four quarters (*SINGLE*), change in non-agricultural employment of the prior four quarters (*EMPLOY*), and the change in per-capita income over the prior four quarters (*INCOME*). The exogenous variables in the various VAR specifications are lagged.