# *Institutional Capital Flows and Return Dynamics in Private Commercial Real Estate Markets*

by

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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 is a vector autoregressive (VAR) regression model in which both institutional capital flows and returns are specified as endogenous variables in a two equation system and in which we also control for various financial and economic variables. At the aggregate U.S. level, where net institutional flows reflect capital being added to the private institutional sector from the non-institutional sector, we find evidence that lagged institutional flows significantly influence subsequent returns. When disaggregating by property type at the national level, we find that capital flows predict subsequent returns in the apartment and office sectors, but not in the retail and industrial markets. At the metropolitan level, we find that flows help explain subsequent returns in a limited number of core business statistical areas (CBSAs), although these CBSAs collectively represent about 30 percent of institutional capital. We find no evidence that institutional returns are predictive of future capital flows at the national or CBSA level, suggesting institutional investors are not chasing returns. Finally, we also document that institutional capital flows into private real estate markets are not generally predictive of future capital flows.

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## Introduction

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, a growing behavioral finance literature is critical of the assumptions of investor rationality and costless arbitrage implied by the efficient market hypothesis. Numerous theoretical models have been developed that recognize limits to arbitrage (supply inelasticities) 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 dedicated mutual fund capital flows in the asset price movements of individual securities and indices.[2] Although the issue is far from settled, several empirical studies suggest a role for capital flows in the pricing of publicly traded stocks and bonds.

In the public commercial real estate sector, 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 predictive of subsequent returns in the REIT sector is uncovered in either study. In this paper, we examine institutional

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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 the 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, Harvey, 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).

capital flows and return dynamics in private commercial real estate markets, which is an important yet unexamined research area to date.

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 and the corresponding lack of such data in private markets. However, the absence 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, approximately 90 percent of investible commercial real estate in the U.S. is owned and traded in private markets.[3] Second, the conventional wisdom among real estate practitioners is that capital flows do directly impact asset prices. In fact, the significant reduction in capitalization rates (initial yields) that occurred in most commercial real estate markets during 2002 to 2007 is largely, if not entirely, attributed to the surge in real estate capital flows that occurred during this period (e.g. Downs, 2007; House, 2004).

However, a contemporaneous correlation between asset prices and capital flows is not sufficient to conclude that flows affect valuations and returns. An alternative explanation is that changes in fundamental economic variables and risk factors—such as per capita income, employment, and interest rates—produce changes in expected property-level cash flows or required rates of returns which, in turn, lead to both higher asset prices *and* increased capital flows and transaction activity (Clayton, 2003; Ling and Naranjo, 2006). Therefore, an observed contemporaneous correlation between property price movements and capital flows does not imply causality.

Why might capital flows influence returns in private real estate markets? Unlike the exchange listed shares of firms "for which close substitutes exist either directly or indirectly" (Scholes,1972), the unique location and other attributes of commercial real estate assets creates highly segmented markets which, in turn, severely restrict an investor's set of acceptable investment substitutes. This segmentation may create markets in which aggregate demand (capital flows) affects valuations—in addition to the marginal investor's assessment of fundamental value (Gompers and Lerner, 2000). For example, an increase in the target

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[3] See Ling and Archer (2008), Chapter 18, page 453.

allocations of pension funds to commercial real estate may result in greater buy-side competition in some metropolitan areas for existing properties, leading in turn to higher prices and short-term returns. This "price pressure" will likely be greatest when pension funds are aggressively growing their real estate portfolios. In addition, the lead time required to bring new commercial properties to the market to meet an increased demand is likely to be significantly longer than the time required to increase the supply of venture capital firms studied by Gompers and Lerner (2000), or other financial assets. The increased price sensitivity to demand shocks that results from an inelastic supply of properties, at least in the short-run, would be observed regardless of whether changing demand is driven by rational or irrational forces.

Although increased capital flows may create price pressure in segmented real estate markets, shifts in capital flows may also reflect changes in investor expectations. That is, increased capital flows into a sector could signal a revision upward in investors' expectations regarding future income streams and/or decreases in investors' required returns—both of which should lead to higher asset prices. In fact, Fisher et al. (2003) argue that transaction volume is predictive of the conditions of local, regional, and national economies. In addition to reflecting changes in investors' rational assessments of fundamental variables, variations in capital flows may, at times, be driven by (irrational) investor sentiment. In short, even in the absence of price pressure, capital flows may capture variation in investor expectations and, therefore, be predictive of future returns.[4]

This paper examines the extent to which institutional capital flows are associated with subsequent returns in a cross-section of U.S. commercial property sectors and geographic markets. Simultaneously, we examine whether the returns earned by institutional investors in private real estate markets impact their subsequent acquisitions and dispositions. Our capital flows and returns are obtained from data supplied by the National Council of Real Estate Investment Fiduciaries (NCREIF). The focus on institutional investors reflects both data availability and the widely held belief that institutional buyers and sellers have different investment motivations and constraints than non-institutional investors, and that institutional investors often

[4] We are not able to separate the price pressure effects of capital flows from signaling effects. For an investigation of the relative pricing roles of fundamentals and investor sentiment in private commercial real estate markets, see Clayton, Ling, and Naranjo (2008).

move into, or out of, markets in herds.[5] Although there may be periods during which the returns of institutional investors are driven, at the margin, by the investment activities of other investor segments, such as REITs or private buyers, the objective of this paper is to quantify the dynamic relation between institutional capital flows and returns.

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 system. We begin with an analysis using national-level institutional capital flows and returns. However, because increases or decreases in institutional capital flows may have differential pricing effects across property types and geographic segments of the private real estate market, we also disaggregate our analysis by property type and by major metropolitan areas.

Our primary findings can be summarized as follows. At the aggregate U.S. level, where net institutional flows reflect the amount of capital flowing into the private institutional sector from the non-institutional sector, we find evidence that the impact of institutional capital flows on subsequent institutional returns is both statistically and economically significant. When disaggregating by property type at the national level, we find that the positive capital flow-return relationship is driven by the office and apartment sectors; we detect no such relation in retail and industrial markets. Furthermore, our metropolitan level analysis reveals that the positive capital flow-return dynamic uncovered at the aggregate U.S. level appears to be driven by a limited number of core business statistical areas (CBSAs), although these CBSAs collectively represent approximately 30 percent of invested institutional capital. Finally, the influence of our control variables is far from consistent across property types and metropolitan areas. This suggests that models intended to predict returns in private real estate market returns must be estimated using data disaggregated to, at least, the metropolitan level.

The remainder of the paper proceeds as follows. In the next section, the VAR methodology we employ to examine the conditional covariation of institutional capital flows and returns is described. We then discuss our data sources and provide a discussion of the descriptive statistics. In the following section, we present our aggregate and disaggregate VAR results. We then discuss the results from various alternative VAR specifications demonstrating the robustness of our major findings. Our conclusions are presented in the final section.

## Research Methodology

We employ vector autoregressive models (VAR) to examine the relationships among institutional investor real estate capital flows and property returns, and we seek to answer two questions.[6] 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?

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. An unrestricted p$^{th}$-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, $\mu$ is a $p$ x 1 vector of intercepts, $\Phi_1$, $\Phi_2$, …, $\Phi_k$ are $p$ x $p$ matrices of parameters with all eigenvalues of $\Phi$ 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 $\Phi$ represent conditional momentum in flows and returns, while the off-diagnol coefficients of $\Phi$ represent conditional positive feedback trading (flows following returns) and conditional anticipation effects (returns following flows). The off-diagnol elements of $\Omega$ capture the price-impact effect of flows on returns.

[5] Several stock market studies find institutions to be informed investors - "smart money" (e.g., Chakravarty, 2001, Jones and Lipson, 2004, and Sias, Starks, and Titman, 2006). However, this evidence is tempered by studies suggesting that institutions do not outperform individual investors (e.g., Nofsinger and Sias, 1999, and Kaniel, Saar, and Titman, 2005).

[6] VAR methods have proven successful for forecasting systems of interrelated time series variables (see Sims, 1980).

We obtain maximum likelihood estimates of $\Phi$ and $\Omega$ 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 are marginal effects.

The above unconstrained VAR system is estimated at the aggregate U.S. level, at the national level by property type, and for a large sample of CBSAs over the 1983:3-2005:2 period using quarterly 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. By separately examining the CBSAs, we are able to disentangle the influence of CBSA location on the conditional dynamics of institutional capital flows and returns.

### *Risk and Macroeconomic Control Variables*

To control for other potential sources of variation in our quarterly return and flow 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 stock market portfolio, as measured by the Center for Research in Securities Pricing (CRSP), minus the corresponding quarterly 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 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

[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.

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 (2003), 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. Ghysels, Plazzi, and Valkanov (2007) provide empirical evidence that the income return (i.e., cap rate) is related to future commercial real estate returns. To control for long-term interest rate levels and trends, we also include the lagged quarterly yield on constant maturity 10-year Treasury securities (*TRYLD*). All else equal, increases in the cost of debt are expected to decrease transaction frequency and property prices, at least in the short run.

Government intervention at the federal, state, and local levels often plays a significant role in real estate markets. For example, growth management and economic development initiatives can vary significantly over time and across local markets. Therefore, we also include several variables intended to control for the economic condition and regulatory environment of the market. In particular, following Fisher et al. (2004) and others we include the change in non-agricultural employment (*EMPLOY*) and the change in per-capita income over the prior four quarters (*INCOME*) to control for the general economic condition of the market. In addition, we include the change in the number of multifamily housing starts (*MULTI*) and the change in the number of single-family housing starts over the prior four quarters (*SINGLE*). These latter two variables are expected to proxy for the condition of the local real estate market, including the cross-CBSA variation in growth prospects driven by the availability of developable land.

Using the risk and macro control variables, 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 examine whether the relations we uncover in our bivariate model are robust to the addition of controls for lagged Treasury yield levels, lagged income returns, and the lagged Fama-French risk factors (*MKT, SMB*, and *HML*). Finally, following Fisher et al. (2004), our eleven-factor model also includes the change in non-agricultural employment, the change in per-capita income over the prior four quarters, the change in the number of multifamily housing starts, and the change in the number of single-family housing starts over the prior four quarters.

## Data and Descriptive Statistics

### *Data Sources and Definitions*

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.[8]

To be included in the NPI, the data contributing member's asset must be an existing property, be at least 60 percent leased, 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 levered properties are included 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.

The NCREIF NPI is the only source of consistently collected information on the total returns earned by investors in private U.S. commercial real estate markets and is therefore widely used as a benchmark of

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

commercial real estate returns. Nevertheless, the NPI has several shortcomings.[9] Of primary concern in the current study is that firms that contribute return data to the NCREIF Index are exclusively institutional investors. Although the acquisition and disposition activities of NCREIF members clearly impact subsequent NPI returns, the investment performance of institutional-quality properties may also be affected by the investment decisions of other investor types, such as foreign investors and private buyers and sellers.

Table 1 provides information on the relative importance of institutional investors in private commercial real estate markets. These data were obtained from Real Capital Analytics (RCA), a national real estate data vendor specializing in tracking commercial real estate transaction activity and prices. The RCA database contains monthly observations on average transaction-based capitalization rates, average per square foot sale prices, and sales volume (both dollar amount and number of properties). Unlike the NCREIF database which tracks the investment activity and return performance on "institutional" quality properties (generally with market values in excess of $10 million), the RCA database captures all transactions in excess of $5.0 million. The RCA data are available since 2001 for approximately 45 major CBSAs by property type. RCA disaggregates all acquisitions and dispositions by investor type: institutional, foreign, public REIT, syndicator, fund, local private investor, and national private investor.

Over the 2001-2006 period, institutional investors have accounted for 18.2 percent of all acquisitions of properties with sale prices greater than $5 million. Only the category of private, in-state, buyers have accounted for a larger share of the total dollar value of acquisitions. REITs and real estate operating companies (REOCs) have accounted for 16.2 percent, on average, of all acquisitions. Clearly institutional investors are a major source of equity capital in private commercial real estate markets.

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

[9] For a detailed discussion of the characteristics of NCREIF's NPI Index, see Geltner and Ling (2007).

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 have sufficient CBSA-level data to construct apartment returns for ten CBSAs. The corresponding number of available 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: (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 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 the four major property types at the aggregate U.S. level, for each of our 43 CBSAs, and for each of our sub-CBSA property type indices.[10]

Finally, 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 as the raw quarterly capital flow in a sector divided by the corresponding total market value of NPI properties in that sector at the beginning of the quarter.

### *Aggregate U.S. Summary Statistics*

Descriptive statistics from the aggregate U.S. dataset are presented in Table 2. 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.

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

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

NPI flows (*FLOWS*) for all NCREIF markets averaged $1.5 billion a quarter. *RFLOWS* averaged 3.09 percent per quarter and displays substantial volatility, ranging from a low of -4.20 percent to a high of 10.99 percent over the study period.

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

Panel A of Table 3 contains the contemporaneous correlations among the variables used in our analysis, along with their statistical significance. The first column in Panel A reveals that aggregate NPI total returns (*RET*) are positively correlated ($\rho$=0.193) with aggregate NPI flows (*FLOWS*). However, *RET* displays no significant contemporaneous correlation ($\rho$=0.018) with *RFLOWS*. Prior empirical studies suggest that commercial real estate returns are likely to be positively correlated with the contemporaneous premiums earned by value stocks. However, the correlation of *RET* with *HML* ($\rho$=0.085) is not statistically significant. Moreover, the correlations among *RET* and *MKT*, *RET* and *SMB*, and *RET* and *TRYLD* cannot be distinguished from zero.

The second column in Panel A of Table 3 reveals that aggregate NPI flows are highly correlated with our constructed measure of relative fund flows (ρ=0.579). NPI capital flows are also positively correlated with *SMB*, but are 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 3 documents evidence of simple univariate relations between the lead and lagged values of our two endogenous regression variables, NPI returns and flows. Aggregate U.S. NPI returns are highly correlated with returns in both prior and subsequent quarters. The high degree of autocorrelation is attributable, at least in part, to the temporal lag bias (i.e., "smoothing") associated with NCREIF returns, which we control for in our conditional regression analysis. In sharp contrast, *RFLOWS* displays no significant correlation with *RFLOWS* in the prior or subsequent quarters.

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 3. Current quarter NPI returns are not significantly correlated with either contemporaneous or lagged flows.

### *Disaggregated Data and Statistics*

Table 4 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. Nominal quarterly capital flows (*FLOWS*) averaged $36.6 million; *RFLOWS* averaged 4.4 percent across the 43 CBSAs.

## Vector Autoregressive Results

### *Aggregate Results*

In this section, we examine the conditional covariation results using return and flow data aggregated across all CBSAs and property types. The first two columns in Table 5 contain the results for the bivariate model. Turning first to the return (*RET*) equations, we find that aggregate NPI returns are influenced by returns in previous quarters. Although not separately 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 institutional returns over the prior four quarters. Given the widely documented autocorrelation (i.e., “smoothing”) in NPI return series, this result was expected.[11]

Controlling for the smoothed nature of NCREIF returns, lagged institutional 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 aggregate *RET* equation. Thus, in the absence of additional control variables, institutional capital flows are not predictive of future NPI returns. Overall, the simple bivariate model is able to explain 62 percent of the variation in current NPI returns.

The seven factor model (column three) includes five additional control variables: the income return on the aggregate NPI in the prior quarter (*INCRET*), the three Fama-French risk factors (*MKT*, *SMB*, and *HML*) and lagged interest rate levels (*TRYLD*). 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 flows in quarters *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 statistically significant. Although the estimated coefficient on *INCRET* is positive and statistically significant, the estimated coefficients on *MKT*, *SMB*, *HML,* and *TRYLD* cannot be distinguished from zero. The adjusted R-squared for the seven-factor total return model is 0.652, a modest increase relative to the bivariate model.

Finally, in column five of Table 5, we report the results of further augmenting the aggregate *RET* equation with our four demographic/market variables: *MULTI, SINGLE, EMPLOY,* and *INCOME.* Including these additional control variables in the estimation increases the adjusted R-squared to 0.777 from 0.652 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. However, the explanatory power of $RET_{t-4}$ actually increases (coefficient of 0.550, t-statistic of 6.012). The sum of the lagged coefficients on *RFLOWS* in the eleven-factor return model is 0.193 with an associated p-value of 0.004.

To examine whether the statistically significant flow effect on returns is also economically significant, we set the independent variables used in the return equation equal to their mean values over the study period. We then multiply the estimated coefficients by these mean values to produce a "predicted" aggregate quarterly return of 2.01 percent (the mean *RET* reported in Table 2 is 2.03 percent). Finally, we shock *RFLOWS* by one standard deviation. This produces a 58 basis point increase (decrease) in the predicted quarterly return, or 231 basis points on an annual basis. Thus, our results suggest lagged institutional capital flows play an economically significant role in explaining the time variation in national-level NPI returns. This result is consistent with the widely held belief among practitioners that capital flows in private real estate markets are predictive of subsequent returns.

We now turn to the capital flow equations 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 NPI returns—at least at the aggregate level. Moreover, *RFLOWS* is not associated with flows over the

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[11] See Fisher and Geltner (2000) and the references therein for a discussion of appraisal smoothing in the context of the

prior three quarters, although the coefficient on $RFLOWS_{t-4}$ is positive and marginally significant. 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*. Nevertheless, the significance of *MKT* and *HML* in the *RFLOWS* equation is not robust to the inclusion of *MULTI, SINGLE, EMPLOY,* and *INCOME* (column 6). Overall, the eleven-factor *RFLOWS* model is able to explain just 1.4 percent of the variation in current flows. Clearly, the prediction of institutional capital flows is difficult at the aggregate U.S. level.

### *U.S. Results Disaggregated by Property Type*

In this section, we examine the conditional covariation results using data aggregated across all CBSAs, but disaggregated by property type. The first two columns in Table 6 contain results for the U.S. apartment sample using the eleven-factor model. The corresponding results for retail, office, and industrial properties are presented in the remaining six columns.

Consistent with the aggregate results presented in Table 5, property level returns are influenced by lagged returns. In the apartment sample, we also find a statistically significant relationship between *RET* and $RFLOW_{t-1}$ and $RFLOWS_{t-2}$. In terms of economic significance, we find that a one standard deviation shock to apartment capital flows produces an economically significant 42 basis point change in the predicted quarterly return (164 basis points annually). In the office sample, $RFLOW_{t-1}$ and $RFLOW_{t-4}$ have a statistically and economically significant effect on current returns. In contrast, none of the individual lagged flow coefficients are significant in the retail or industrial *RET* equations, suggesting that the significant flow-return relations uncovered in the aggregate U.S. regressions is driven primarily by apartment and office properties.

The estimated coefficients on the lagged NPI income return and the Fama-French factors are not significant in any of the four property type VAR specifications. However, returns are negatively and significantly related to the lagged Treasury yield. Moreover, *MULTI* and *EMPLOY* are positively and significantly related to returns in all but the retail RET estimation.

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NCREIF Index.

Examination of the *RFLOWS* estimations confirms our prior finding of no significant role for lagged flows or lagged returns in explaining current flows. Although the adjusted R-squared of the apartment *RFLOWS* equation is 0.182, institutional capital flows remain difficult to predict at the aggregate U.S. level.

### *Results Disaggregated by CBSA*

As reported above, we find conditional evidence using national-level data that both lagged returns and capital flows predict subsequent returns to institutional real estate investors. We also find evidence that lagged returns and flows influence subsequent returns for apartment and office properties, although not for industrial and retail properties. These results suggest that the effects of capital flows on returns may depend on the motivations for institutional investors to purchase properties in a particular property sector. The next question we examine is whether the institutional capital flow-return dynamic varies across CBSAs. To answer this question, we separately estimate our eleven-factor VAR model for each of the forty-three CBSAs in our sample. In Table 7 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.[12]

The first two rows in the top panel of Table 7 contain our "All Property Type" results for the return equations. 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 NPI returns is statistically significant in 91 percent of the CBSA return regressions.

The national-level regressions reported in Table 5 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 7 suggest this aggregate result may be driven by a limited number of the forty-three CBSAs, although as noted below these CBSAs represent about 30 percent of the sample. More specifically, the

[12] Although the use of a 5 percent significance level would be more restrictive, we chose a 10 percent significance level to increase the likelihood of finding a statistically significant relation between flows and returns, particularly in light of our

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. Looking at the cumulative four quarter effect of flows on returns, we find that returns in just 23 percent of the CBSAs are influenced by cumulative lagged flows. Taken together, these results reveal a great deal of variation across CBSAs in the impact of NPI capital flows on subsequent returns. It is notable that several of the CBSAs where we do find a relationship between lagged capital flows and returns were those CBSAs that represent a significant proportion of the institutional capital in the NCREIF database.

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 43 CBSA 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 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 7. 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 institutional capital flows is a difficult task.

### *Results Disaggregated by Property Type at the CBSA-level*

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results suggesting that there is a somewhat limited effect. If we instead use 5 percent significance levels, the proportionate significant coefficient effects are approximately 80 percent of those reported in Table 7.

It is possible that our CBSA-level results are 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 CBSAs where sufficient NCREIF data are available. More specifically, we identified 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 to estimate separate retail, office, and industrial VAR models.

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. Overall, the property level regressions provide evidence of significant variation across property types in the dynamic relation between capital flows and returns and in the importance of CBSA control variables.

## Some Additional Robustness Checks

We performed various robustness checks on the conditional relation between NPI flows and subsequent returns. In particular, we examined the stationarity of the variables, various structural VARs, the 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 institutional markets, the effects of replacing NCREIF total returns with the portion attributable to nominal price appreciation (i.e., the capital gain), the effects of using the transaction-based index (TBI) of NCREIF returns produced by MIT in place of the NPI, the effects of using alternative market risk factors and lags, potential asymmetric and nonlinear effects. Though not tabulated, we describe below the results corresponding to these various robustness checks.

To insure we are using the appropriate dynamic model, we examined whether our capital flow and return time series variables are stationary, as non-stationarity would require the use of a vector error-correction (VEC) model.[13] Unit root tests indicated that the various series were stationary.

We also estimated various structural VAR models (i.e., restricted VARs) where we impose various identifying restrictions, including specifying current NPI returns related to current flows (as well as both past returns and flows) and current flows related to current NPI returns. We find that current flows explain current returns and that current returns explain current flows. However, contemporaneous flow-return effects are highly sensitive to model specification (variables included and restrictions), the sample period, the estimation algorithm, and starting values used. Although contemporaneous flow-return effects are unstable, the estimated coefficients on the remaining variables are similar to those reported in Table 5.

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. Overall, we find little time variation in the influence of NPI flows on NPI returns and vice versa. In particular, we find a very small decrease in the number of CBSAs in which NPI returns influence returns, flows influence returns, and returns influence flows. The frequency of flows influencing flows remains constant over each of the sub-periods.

The potential influence of lagged real estate investment trust (REIT) returns on NPI returns and flows is also examined. REIT returns, as captured by the National Association of Real Estate Investment Trust (NAREIT) Equity Index, have an insignificant effect on both institutional flows and returns. More specifically, the t-statistics on the NAREIT coefficients were insignificant in the aggregate U.S. specification. Moreover, inclusion of NAREIT returns did not affect the influence of other variables in the specification. At the CBSA level, the inclusion of NAREIT returns also did not change our reported results.[14]

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[13] 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.

[14] This result is consistent with many prior analyses of the relation between returns in public and private commercial real estate markets. See, for example, Clayton and MacKinnon (2003) and the references cited within.

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). The use of this alternative flow variable yields similar results to those reported above. For example, in Table 7 the summed effect of flows on returns is significant in 23 percent of the CBSAs, whereas it is significant in 20 percent of the CBSAs using the across market relative specification.

Examination of Table 2 reveals that the primary driver of NCREIF total returns is the income component. Due to the existence of multiple-year leases on most property types, it could be argued that the income component is relatively sticky and not affected by capital flows and trading intensity, at least in the short run. Thus, any price pressure caused by capital flows would presumably influence only transaction prices. To address this issue, we redid our analysis using the appreciation component of the NPI total return in place of the total return. The results are very similar to those reported in the paper. There is, however, a small increase (less than 10 percent) in the number of times cumulative lagged flows are significant in the CBSA-level return equation. It is important to note that the lagged income return is included as an explanatory variable in our preferred VAR specifications. Thus, by controlling for the income return, our estimation framework picks up the effects of capital flows and other exogenous variables on the appreciation return component.

We argue above that by including four quarters of lagged NPI returns in our return and capital flow equations we are effectively controlling for the well-documented appraisal smoothing/lagging nature of NCREIF returns. As an additional robustness check, however, we re-ran our national/aggregate analysis using the transaction-based index (TBI) of NCREIF returns produced by MIT's Center for Real Estate in place of the NPI. The MIT/CRE TBI is constructed to measure market movements and returns based on transaction prices of properties sold from the NCREIF Index database. Therefore, it can be argued that the TBI may provide a more accurate picture of price movements.[15] Using the TBI produces similar results, although the statistical significance of *RFLOWS* in the aggregate return equation declines somewhat.

[15] The TBI estimates quarterly market price changes based on the verifiable sales prices of all properties sold from the NPI database each quarter. The TBI is a hedonic price index that controls for differences in the properties that are sold

We also examined the residuals from an AR(1,4) of NPI returns in place of NPI returns. It is important to note that our VAR estimation, in effect, captures these scaled returns since we use four lags in our VAR analysis. However, if we instead use the residuals from an AR(1,4) process in place of lagged returns, the statistical significance of lagged flows in the return regressions declines modestly.

Our selection of *MKT* as a control variable is based on the current state of the art in empirical asset pricing research, as is our use of the Fama-French factors. However, to further address the robustness of our primary results, we tried various alternative specifications of the excess market return variable. In particular, we examined both recent and cumulative market returns, lagged market returns, the change in market returns over the year, and the volatility of excess market returns. The only alternative specification that was marginally significant (at the 10 percent level) was lagged market returns, although it did not materially influence any of the reported results.

To test for nonlinearities in the relation between flows and returns, we added squared capital flows and squared returns to the eleven factor model. We find that the squared variables are significant in less than eight 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 five 5 of the 43 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 of greater importance for the flows specification than the returns specification.

## Summary and Conclusion

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. Although the importance of capital flows in asset pricing has received significant attention in public

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each period, for transaction sample selection bias, and for estimation error noise. The details of the index methodology securities markets, 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 because of the size of the private commercial real estate market and because the supply inelasticities inherent in commercial real estate markets should make asset prices and returns in these markets more susceptible to exogenous demand shocks.

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 from the National Council of Real Estate Investment Fiduciaries (NCREIF) 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 also disaggregate our national analysis by property type. Next, we examine whether net new capital invested in 43 metropolitan areas by members of NCREIF is associated with higher, or lower, institutional 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.

At the aggregate U.S. level, where net institutional capital flows reflect capital being added to the private institutional sector from the non-institutional sector, we find evidence that institutional capital flows have a statistically and economically significant association with subsequent returns. This result is consistent with the widely held belief among practitioners that capital flows in private real estate markets are predictive

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are described in Fisher, Geltner, and Pollakowski (2007).

of subsequent returns. When disaggregating by property type at the national level, we find that institutional capital flows predict subsequent returns in the apartment and office properties sectors, but not in retail and industrial markets. This may reflect differences by property type as to whether institutional or non-institutional investors were the "marginal investor" during the time period studied.

When evaluating the results for individual CBSAs, we find evidence of flows predicting subsequent returns in only a limited number of CBSAs, although these CBSAs collectively represented about 30 percent of the market value of the NCREIF database. Because some of the net capital flows into property sectors and CBSAs represent movement of institutional capital from one property sector or CBSA to another, these flows may not have the same impact on prices as new institutional capital coming into the market from the non-institutional sector.

We find no evidence that returns are predictive of future institutional capital flows. We also document that institutional capital flows are not generally predictive of future capital flows. Thus, 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 2001 from Real Capital Analytics may prove to be helpful in this effort.

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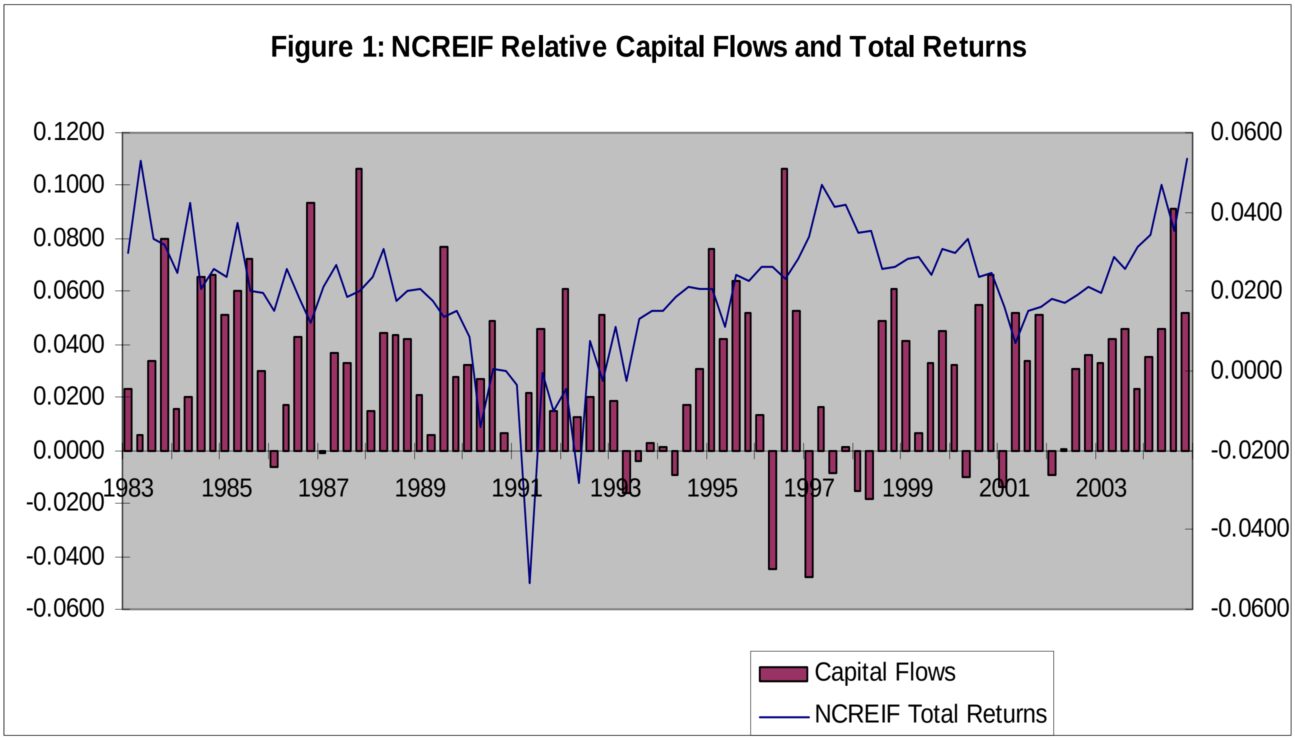

Figure 1: NCREIF Relative Capital Flows and Total Returns
0.1200
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
-0.0600
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
-0.0600
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
Capital Flows
NCREIF Total Returns

[redacted]

Data obtained from Real Capital Analytics, a national real estate data vendor specializing in tracking commercial real estate transaction activity and prices. The RCA database contains monthly observations since 2001 on average transaction-based capitalization rates, average per square foot sale prices, and sales volume (both dollar amount and number of properties) for all transactions in excess of $5.0 million in the approximately 45 major metropolitan areas they follow. RCA disaggregates all acquisitions and dispositions by investor type: institutional, foreign, public REIT, syndicator, fund, local private investor, and national private investor.

[redacted]

[redacted]

**Table 4**

[redacted]

[redacted]

**Table 5**
**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) | (1.640) | (-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 5 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, $\Phi_1$, $\Phi_2$, …, $\Phi_k$ 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,Ω)]. 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 6**

**Aggregate Property-Level Vector Autoregressive Model Estimates: 1983:3-2005:2 (quarterly)**

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

| Variables | Apartments | | Retail | | Office | | Industrial | |
|---|---|---|---|---|---|---|---|---|
| | *RET* | *RFLOWS* | *RET* | *RFLOWS* | *RET* | *RFLOWS* | *RET* | *RFLOWS* |
| Constant | 2.429* | 1.715* | 2.910 | 1.270* | -1.502 | 1.133 | 1.854 | 1.866** |
| | (1.858) | (1.770) | (1.574) | (1.652) | (-0.861) | (1.438) | (1.295) | (2.043) |
| $RET_{t-1}$ | 0.202* | -0.675 | 0.071 | -0.210 | -0.004 | 0.349 | -0.037 | -0.020 |
| | (1.759) | (-0.795) | (0.549) | (-0.389) | (-0.044) | (0.807) | (-0.264) | (-0.022) |
| $RET_{t-2}$ | 0.140 | 0.457 | 0.490** | 0.226 | 0.082 | 0.627 | 0.333** | 0.469 |
| | (1.178) | (0.519) | (3.809) | (0.421) | (0.847) | (1.429) | (2.369) | (0.523) |
| $RET_{t-3}$ | -0.041 | -1.520* | 0.19 | -0.125 | -0.068 | -0.737* | -0.086 | 0.746 |
| | (-0.346) | (-1.719) | (0.139) | (-0.213) | (-0.756) | (-1.808) | (-0.588) | (0.799) |
| $RET_{t-4}$ | 0.296** | 0.341 | 0.583** | 0.424 | 0.583** | 0.237 | 0.481** | 0.260 |
| | (2.550) | (0.397) | (4.341) | (0.758) | (6.778) | (0.610) | (3.726) | (0.315) |
| $RFLOWS_{t-1}$ | 0.036** | -0.122 | 0.031 | -0.090 | 0.048* | -0.069 | 0.027 | -0.057 |
| | (2.328) | (-1.063) | (1.122) | (-0.773) | (1.842) | (-0.587) | (1.404) | (-0.461) |
| $RFLOWS_{t-2}$ | 0.029* | -0.134 | 0.002 | 0.047 | 0.034 | -0.067 | 0.029 | -0.205* |
| | (1.808) | (-1.149) | (0.194) | (0.978) | (1.534) | (-0.669) | (1.511) | (-1.670) |
| $RFLOWS_{t-3}$ | -0.001 | 0.022 | 0.009 | -0.022 | 0.026 | -0.055 | 0.014 | -0.131 |
| | (-0.064) | (0.183) | (0.957) | (-0.548) | (1.291) | (-0.607) | (0.762) | (-1.154) |
| $RFLOWS_{t-4}$ | -0.006 | 0.249** | 0.011 | 0.014 | 0.040** | -0.697 | 0.029 | -0.018 |
| | (-0.397) | (2.158) | (1.110) | (0.351) | (2.008) | (-0.781) | (1.630) | (-0.155) |
| *INCRET* | -0.351 | -6.343* | -0.789 | -4.680 | 1.241* | -4.065 | -0.214 | -8.120** |
| | (-0.698) | (-1.703) | (-1.099) | (-1.567) | (1.813) | (-1.314) | (-0.370) | (-2.205) |
| *MKT* | -0.017 | 0.203* | -0.021 | 0.157** | 0.027 | 0.083 | 0.009 | 0.061 |
| | (-1.134) | (1.815) | (-1.140) | (2.025) | (1.599) | (1.069) | (0.745) | (0.763) |
| *SMB* | 0.022 | -0.120 | -0.002 | -0.156 | 0.015 | 0.136 | 0.021 | 0.005 |
| | (0.971) | (-0.711) | (-0.052) | (-1.294) | (0.530) | (1.090) | (0.981) | (0.039) |
| *HML* | 0.008 | -0.004 | -0.001 | 0.138 | 0.029 | 0.127 | 0.017 | 0.056 |
| | (0.538) | (-0.034) | (-0.035) | (1.618) | (1.511) | (1.453) | (1.214) | (0.618) |
| *TRYLD* | -0.218** | 0.327 | -0.241** | -0.193 | -0.345** | -0.034 | -0.305** | 0.407 |
| | (-3.401) | (0.691) | (-2.377) | (-0.456) | | (-0.086) | (-4.578) | (0.959) |
| *MULTI* | 0.017** | -0.051 | 0.009 | -0.008 | 0.018** | -0.010 | 0.015** | 0.030 |
| | (2.545) | (-1.008) | (1.094) | (-0.024) | (2.137) | (-0.266) | (2.605) | (0.837) |
| *SINGLE* | 0.012 | -0.029 | 0.012 | -0.011 | -0.007 | -0.005 | -0.005 | -0.590 |
| | (1.292) | (-0.422) | (0.877) | (-0.204) | (-0.587) | (-0.091) | (-0.590) | (-1.174) |
| *EMPLOY* | 0.212* | 0.947 | 0.139 | -0.122 | 0.301** | 0.204 | 0.301** | -0.585 |
| | (1.776) | (1.070) | (0.991) | (-0.209) | (2.258) | (0.339) | (2.907) | (-0.887) |
| *INCOME* | -0.001 | -0.037 | -0.035 | 0.050 | 0.192* | 0.016 | 0.122 | -0.437 |
| | (-0.009) | (-0.055) | (-0.311) | (0.107) | (1.749) | (0.033) | (1.512) | (-0.847) |
| Adj. R-squared | 0.524 | 0.182 | 0.646 | 0.037 | 0.805 | 0.005 | 0.761 | 0.021 |

## Table 6 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, $\Phi_1$, $\Phi_2$, …, $\Phi_k$ 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,Ω)]. We obtain maximum likelihood parameter estimates using iterated least squares. For each of the property types aggregated at the national level, we estimate an eleven-factor model. The eleven factor model consists of total capital flows and aggregate returns within each property type, 10-year CMT yields, NCREIF income returns for each property type, 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.

## Table 7

**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 7 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, $\mu$ is a $p$ x 1 vector of intercepts, $\Phi_1, \Phi_2, \ldots, \Phi_k$ are $p$ x $p$ matrices of parameters with all eigenvalues of $\Phi$ 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.