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# The Motivation for Institutional Real Estate Sales and Implications for Asset Class Returns

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Since real estate assets are sold infrequently, analyses that use samples of exclusively sold properties to estimate pricing models may be seriously in error. This paper uses data on samples of sold and unsold properties and an appropriate statistical methodology to evaluate the extent of this bias. The results clearly show that it is important to control for sales motivations and that pricing equations that ignore this source of bias may be misleading.

## INTRODUCTION

One of the more interesting and most neglected questions relating to commercial real estate is why one property in a portfolio is sold while another, seemingly similar property, is not sold. The neglect stems from the paucity of market transaction data. Recently, major commingled real estate fund managers have made available such data on 277 investment-grade properties that are diversified across such dimensions as size, type, location, and date of sale. Using data from these sold properties and from a similar sample of 192 unsold properties currently held in the portfolios of these same managers, this study attempts to determine statistically whether sold properties differ in a systematic way from unsold properties.

An understanding of the motivation for sales is important to an understanding of commercial real estate returns in general. Because of the infrequency of trades and limited disclosure of sales information,

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commercial real estate returns are usually estimated from fairly small samples over relatively short time horizons.[1] Before attempting any generalizations from such limited data, it is important to identify possible biases that might require statistical adjustments and/or interpretational qualifications. This research attempts to address the issue of such potential biases by enumerating the logic supporting sales of certain types of property (see section two) from an extensive database (section three) using well-known methodology (section four). The results (section five) confirm the existence of systematic differences in sold versus unsold properties. The conclusions (section six) suggest the necessity of caution in generalizing from the results of previous work using samples of sold properties to proxy for market returns.[2]

## MODEL SPECIFICATION

### *Potential Sales Motivations*

There exist a number of potential sales motivations that are hypothesized to explain why a fund manager may choose to sell a particular property. Theoretically, these hypotheses may be categorized as either informational asymmetries or agency issues.

H1. The manager/seller may simply have a less optimistic forecast of the property's future value than the potential buyer. In a market characterized by informational asymmetries, both the buyer and seller may believe that they have superior information justifying the transaction.

H2. The fund manager may sell one or several properties to meet his liquidity needs, i.e., to honor withdrawal requests that exceed current income (or in the case of closed end finite life funds because the fund came to the end of its stipulated life).

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[1]See Hartzell, Hekman and Miles [1987] for a discussion of these issues.

[2]Hoag [1980] developed a real estate index from industrial property sales. The results were intuitively appealing in that the coefficient of variation associated with this return series placed real estate returns in a more reasonable position relative to stocks and bonds than had the results of previous appraisal-based studies. However, Hoag made no effort to determine if his sales were representative of the entire class of property and, therefore, his results could be far from generalizable.

H3. Sales may be motivated by issues relating to managerial efficiencies. Asset management is relatively more expensive for small than large properties, so that managers may sell off the smaller properties in their portfolio in order to purchase larger ones, thus reducing their internal operating expenses. When funds have limited capital, managers may find it necessary to purchase smaller properties in order to diversify risk. However, as the sizes of funds grow, managers may find it desirable to liquidate many of these smaller properties in favor of their larger counterparts.[3]

H4. Operational logistics may also dictate that a manager should sell off a property that is geographically located far away from the bulk of the properties in that manager's portfolio. Because information is both critically important and expensive, due to the local nature of real estate markets, it may be cheaper to concentrate managerial resources on a large number of properties located in a few markets rather than a small number of properties located in many markets.[4]

To investigate hypothesis H1 above, a series of socioeconomic variables are used to proxy for both current supply/demand conditions and expected changes in such conditions. By using contemporaneous public statistics that are available only well after the quarter in question, this work captures what might be labeled as a "locally-informed perspective." There is no claim of market inefficiency, rather there is one of informational asymmetry.

The last three hypotheses all relate to the needs and objectives of the investment manager, which may not be identical to the needs and objectives of the investor—e.g., if the investor's marketing is ineffective, then there may be a liquidity problem at the investment level that does not parallel any similar need at the investor level. These

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[3]In perfectly efficient markets, one might expect the cost of such management to be impounded in the price. However, over this period of time, pension funds dramatically increased their collective investment in commercial real estate so that management economies changed with the new ownership, creating the phenomenon described here.

[4]Miles and McCue [1984] and Hartzell, Hekman and Miles [1986] found that diversification benefits can be achieved within geographic regions, even using naive strategies. Other property-specific characteristics such as property type, size, lease structure, and location within a particular market differ and may dominate regional market similarities (such as changes in population, employment, and income) leading to relatively low levels of systematic risk in any broadly defined geographic region.

agency-related sales motivations are captured by using appropriate measures for each of the three hypotheses H2-H4 cited above.

In investigating all four hypotheses, separate probit equations are needed for each basic property type because the values of the different property types are functions of different variables that may lead to differences in sales motivations across property types.

*Modeling Sales Prices*

In order to fully understand the implications of generalizing from limited samples of sold properties to asset-class returns that are valid for all properties, it is not enough to test empirically the potential sales motivations suggested above. One must also test for bias in the pricing equation due to estimation from a sample of only sold properties. In a companion paper, the authors hypothesize that prices for the four major types of commercial real estate can be modeled using variables related to 1) the location of the property in the specific market, 2) the location of this market in the nation, 3) the operating history of the property, 4) the physical condition of the property, and 5) the nature of any existing leases. Specifically, office building prices are modeled as a function of the number of stories (a proxy for centrality in market location), change in county population (market's location relative to the nation as a whole), historic property cash flows (operating history),[5] the amount of capital improvements and the holding period (physical condition of the property), and the number of major credit tenants and percentage expense pass-throughs relative to lease maturity (impact of existing leases).

The pricing equations for retail properties, industrial properties and industrial "upgrade" (R&D) properties are similarly based on the same five hypothesized determinants of value. However, the variables proxying for each determinant of value change to reflect differences among property types. For example, distance to an interstate highway is a critical market location variable for industrial but not office properties. Similarly, change in per capita income is a better measure of expectations for the markets' quality (in-nation location) for retail properties while change in wholesale earnings is a better measure for

[5]Also changing quarterly is a capitalization rate that produces a value from these historic cash flows. The capitalization rate is an attempt to model broader "market factors" in the pricing of the properties. Ideally, the impact of changing tax laws over the sample period would also be modeled. Unfortunately, data limitations preclude the investigation of this potentially important but very complex issue. (See Follain, Hendershott and Ling [1987] for a discussion of related issues.)

industrial properties. (See Miles, Guilkey and Cole [1988] for a fuller description of the pricing equations.)

When these price functions are jointly estimated with a probit equation developed from the sales logic discussed in the first part of this section, the extent of the sample selectivity bias that would be present in a single equation estimation of the price equation can be determined. If the measure of correlation between the two equations (sales price and likelihood of sale) is significant, then variables omitted from both specifications are important in each and the ordinary least squares estimates of the price equation would be incorrect. In such a case, parameter estimates for the price equation should be obtained from joint estimation of the probit equation with the sales equation.

## DATA

The data used in this study include the operating histories of 573 non-farm income-producing properties taken from the FRC Property Index.[6] This index has become the standard for evaluation of institutional real estate and is widely quoted in the *Wall Street Journal* and various investment banking publications. To qualify for inclusion, a property must be held in a tax-exempt portfolio and must not be levered.[7]

These properties are divided into two samples. The first, which will be referred to as the sold property sample, consists of 347 FRC properties sold between January 1978 and December 1986. The second, which will be referred to as the control sample, consists of 226 FRC properties that figured into FRC Property Index calculations as of December 1985.[8]

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[6]The FRC Property Index was created by the National Council of Real Estate Investment Fiduciaries and the Frank Russell Company to establish an industry-wide benchmark for real estate performance. The initial database, created in December 1977, consisted of 236 properties with an aggregate market value of $594 million. As of December 1986, the Index consisted of 1,001 properties with an aggregate value of $11.19 billion assembled from the portfolios of life insurance separate accounts, bank trust departments, and individual money managers.

[7]The database consists of investment-grade income-producing properties including office, retail, industrial, apartment, and hotel establishments. Development properties are only included one year after competition or after reaching at least 80% occupancy. Joint ventures may be included only if reported as if individually owned.

[8]The random control sample was chosen as follows: All sold properties and all of the remaining properties were separately sorted and counted by year of initial inclusion in the FRC Index. (As of December 31, 1985, there were 226 reported sales.) A random sample of 226 unsold properties was taken from the

In the course of the data collection process, it was determined that 70 properties from the sold sample and 34 properties from the unsold sample were unsuitable for use in this study.[9] These 104 properties were deleted from the database, leaving 277 and 192 properties in the sold and unsold samples, respectively. Both of these samples and the FRC Property Index in total are well diversified across a number of dimensions, such as property type, location, investment manager, and size.

For each sample property, data relating to financial history, lease terms, physical structure, and location (both national and within the metropolitan area) were collected. Importantly, all properties are identified by county. Such identification by county allows for the testing of considerable urban economic theory because quarterly information from other databases (such as those of the Census Bureau, the Bureau of Labor Statistics, and the Bureau of Economic Analysis) are also collected by county.

Detailed financial performance data were collected from the FRC Property Index records. These data consist of quarterly observations on each property for the variables: net income, capital improvements, partial sales, and appraised value.

In addition to the quarterly socioeconomic data and financial history, property-specific "fixed" data such as number of stories, distance to major transportation arteries, and physical age were collected from

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pool of all unsold properties so that, for each year of initial inclusion, the numbers of properties in the sold sample and in the random unsold sample were the same. In early 1987, all properties sold in 1986 were added to the database, increasing the number of sold properties to 347. For reasons explained in footnote 10, 70 sold and 34 unsold properties were deleted, leaving 277 useable sold and 192 useable unsold properties in the database.

[9]Seventy sold properties were deleted from the database. Twenty-nine involved complex below market financing and/or income guarantees or multiple property sales; twelve sales were, in reality, consolidations or renumberings of properties that had not actually been sold; five sales were not "arms-length" transactions; two sales involved properties with multiple nonadjacent locations; data for ten sales were unavailable and presumed by fund managers to be lost; data for twelve sales that occurred in late 1986 were also unavailable in time for inclusion in this study. Thirty-four unsold properties were deleted. Twenty-eight were sold during 1986 so that they were moved to the sold sample. Two involved complex partnership arrangements. One had multiple nonadjacent locations. Detailed supporting documents for three properties were unavailable and presumed by fund managers to be lost.

In Tables 2 through 5, the number of observations vary from the weighted probits because four sold and two unsold properties were classified in more than one type. Four properties were classified as both industrial warehouse and industrial R&D, one as office and retail, and one as retail and industrial R&D. Thus, number of sold and unsold observations in these tables add up to 281 and 194 instead of 277 and 192, respectively.

the detailed internal records of the individual investment managers. For each property, the data span the entire period for which the property entered into FRC Index calculations. Each of these observations was confirmed both by the investment fund manager and by the researchers during personal visits to each fund manager.

Table 1 presents descriptive statistics for the sample used in the multivariate analysis. This unweighted set of statistics includes all four property types.

## METHODOLOGY

### *Weighted Probit*

Standard regression methods cannot be used to analyze the factors affecting whether or not a property is sold because the dependent variable is discrete—i.e., a property is sold or it is not sold. Thus, a probit maximum likelihood estimation procedure is employed in the analysis.[10] Even though this is a nonlinear method, equation (1) is written in linear form for the sake of exposition:

$$S_i = X_i\beta + \epsilon_i \qquad i = 1, 2, \ldots, N \tag{1}$$

where

$S_i$ = 1 if the property belongs to the sold sample
= 0 if the property belongs to the control sample[11]
$X_i$ = a vector of independent variables representing property and location characteristics.
$\beta$ = a vector of parameters to be estimated
$\epsilon_i$ = a normally distributed random disturbance term with mean zero and variance one[12]
$N$ = sample size.

The estimation procedure is further complicated by the fact that while all eligible sold properties are included in the database, only a

[10]Computations were carried out using the LIMDEP statistical package developed by Greene [1985]. Starting values are obtained from least square estimates. Newton's method of estimation is then used to obtain final values of parameter coefficients. The covariance matrix for coefficients is estimated as the second derivative of the log-likelihood.

[11]For a detailed description of the probit and other binary choice models, see Judge et al. [1985] or Kmenta [1986].

[12]Clearly, $\epsilon_i$ cannot follow a continuous distribution if $S_i$ can only take on the values of zero and one. The probit model hypothesizes that there exists an underlying continuous variable that is the true dependent variable and that $S_i$ is its observed discrete realization. See Judge et al. [1985] or Kmenta [1986] for a more detailed description.

**TABLE 1**

**Summary Statistics**

| Variable | *N* | Mean | Standard Deviation |
|---|---|---|---|
| Capitalization Rate (*CAPRATE*) | 277 | 0.01804 | 0.00092 |
| Population (*POP*) in Millions | 469 | 1.758 | 2.117 |
| Income per Capita (*YPC*) in Thousands | 469 | 15.31 | 3.086 |
| Construction Earnings per capita (*CON*) in Thousands | 469 | 0.7044 | 0.2275 |
| Manufacturing Earnings (*MFG*) in Thousands | 469 | 2.714 | 1.525 |
| Wholesale Earnings (*WHS*) in Thousands | 469 | 1.004 | 0.5443 |
| Unemployment Rate per capita (*LUR*) % | 469 | 0.06253 | 0.02168 |
| Change in Population (*CPOP*) | 469 | 0.01380 | 0.01436 |
| Change in Income per Capita (*CYPC*) | 469 | 0.05431 | 0.02322 |
| Change in Unemployment Rate (*CLUR*) | 469 | −0.01980 | 0.1531 |
| Change in Construction Earnings (*CCON*) | 469 | 0.08208 | 0.06936 |
| Change in Manufacturing Earnings (*CMFG*) | 469 | 0.03492 | 0.03859 |
| Change in Wholesale Earnings (*CWHS*) | 469 | 0.05180 | 0.04665 |
| Change in Finance, Insurance and Real Estate Earnings (*CFIR*) | 469 | 0.1279 | 0.04721 |
| Change in Service Earnings (*CSVC*) | 469 | 0.08803 | 0.02659 |
| Number of Stories (*STORIES*) | 469 | 2.115 | 3.592 |
| Number of Buildings (*BLDGS*) | 469 | 1.947 | 4.439 |
| Central Business District (*CBD*) 0-1 | 469 | 0.04691 | 0.2117 |
| Free Standing (*FS*) 0-1 | 469 | 0.1279 | 0.3344 |
| Net Square Footage (*NETSF*) in Thousands | 469 | 113.09 | 119.3 |
| Distance to Highway (*DHIWAY*) in miles | 469 | 1.269 | 0.7654 |
| 0 = adjacent | | | |
| 1 = 0-1 mile | | | |
| 2 = 1-5 miles | | | |
| 3 = >5 miles | | | |
| Number of Tenants (*TENANTS*) | 469 | 16.29 | 50.37 |
| Major Credit Tenants (*MAJORCR*) 0-1 | 469 | 0.2495 | 0.4332 |
| Mixed Credit Tenants (*MIXEDCR*) 0-1 | 469 | 0.2431 | 0.4294 |
| Minor Credit Tenants (*MINORCR*) 0-1 | 469 | 0.4392 | 0.4968 |
| Lease Maturity (*LEASEMAT*) in years | 469 | 4.558 | 5.032 |
| Percentage of Expense Increases Passed Through to Tenants (*PCTPASS*) | 469 | 82.88 | 31.63 |
| Age of Building(s) (*AGE*) in years | 469 | 10.89 | 8.305 |
| Percentage of Finished Office Space (*PCTOFF*) — Industrial only | 469 | 0.1138 | 0.2022 |
| Holding Period (*HOLDPER*) in 10th of years | 469 | 72.51 | 32.22 |
| Gross sales Proceeds per Square Foot (*GSF*) $ | 469 | 24.765 | 30.915 |
| Stabilized Income per Square Foot (*YSTABSF*) $ | 469 | 1.123 | 0.8743 |
| Actual Income per Square Foot less *YSTABSF* (*LOWYSF*) $ | 469 | 0.2651 | 0.5763 |
| Capital Improvements per Square Foot (*CAPSF*) $ | 469 | 0.3090 | 1.062 |
| *LEASEMAT* greater than 5 years and *PCTPASS* greater than 70% (*BOND*) 0-1 | 469 | 0.2793 | 0.4491 |
| *YSTABSF* greater than 2.0, Industrial Warehouse only (*HIINCOME*) 0-1 | 178 | 0.1815 | 0.4420 |

chosen subset of the unsold properties are included. Therefore, choice-based sampling methods must be used to correct for the non-random nature of the sample. Essentially, this estimation procedure involves the use of a weighted likelihood function, where the weights for the sold and unsold properties are determined by their actual frequencies in the set of all properties.[13]

### *Joint Estimation*

The statistical form hypothesized for the sales price equations is.

$$V_i = Z_i\gamma + u_i \qquad i = 1, 2, \ldots, M \tag{2}$$

where

$V_i$ = sales price per square foot for property $i$
$Z_i$ = a vector of independent variables representing property and location characteristics
$\gamma$ = a vector of parameters to be estimated
$u_i$ = a normally distributed random disturbance term with mean zero and variance $\sigma^2$ for all values of the independent variables
$M$ = sample size where $M < N$ is the number of properties in the sold sample.

The method of estimation that has been used in the past for equations such as (2) has been ordinary least squares (OLS) or some variant. Unfortunately, OLS can lead to seriously biased coefficient estimates if the sample is not random. Clearly, a sample of properties that have been sold recently may not be representative of the universe of properties. If one can control for the non-random nature by a complete specification of all variables that determine value (i.e., $Z$ represents a

[13]In this sample, sold properties are overrepresented so that they constitute 59% of the sample while unsold properties are underrepresented so that they constitute 41% of the sample. The FRC population from which the sample was drawn contains 347 sold and 1001 unsold properties. Thus, the sample sold properties are overrepresented by a factor of 2.29 while the unsold properties are underrepresented by a factor of .551. In order to correct for this bias, it is necessary to scale down the sold properties by a facter of .436 and to scale up the unsold properties by a factor of 1.814. This same logic was used to come up with analogous weighting for each of the four property types. In order to obtain the correct covariance matrix for the parameter estimates from this weighted estimation, the following procedure was used. First, $H$ and $G$ were calculated, where $H$ was the negative inverse of the Hessian of the weighted log likelihood and $G$ was the summed outer products of the first derivatives of the weighted log likelihood. Then the correct covariance matrix $V$ was calculated as $V = [GHG]^{-1}$. See Maddala [1983] for a more complete treatment.

complete set), then OLS is still appropriate. This ideal situation will almost never hold in practice because there is always the possibility of omitted variables not observable in any data set that determine both value and the likelihood of sale. The statistical implication of this fact is that the error terms in equations (1) and (2) will be correlated due to this overlap in omitted variables so that OLS on equation (2) will be incorrect.

The correction to this type of problem was developed by Heckman [1979], and a textbook discussion of the correction can be found in Maddala [1983]. Heckman suggested two procedures. The first method uses the probit results from equation (1) to "correct" the disturbance of equation (2) so that a heteroskedasticity-corrected OLS can be used. The second method involves the joint estimation of equations (1) and (2) by maximum likelihood methods. In this study, the maximum likelihood method is chosen because it is the asymptotically efficient procedure (see section six).

## PROBIT RESULTS

In estimating the sales equation for each of the four property types, the model specifications are not identical. There are both theoretical and empirical explanations for these differences. The theoretical reasons why one particular variable may be more important than another for a specific property type are discussed above. The specifications used are the result of first estimating each equation with a larger number of variables and then dropping variables whose *t*-statistics were less than 1 in absolute value so that a more parsimonious set of results could be discussed.

The detailed probit results are not presented (to conserve space) because those equations were reestimated as part of the joint estimation procedure. The simple probits and the probits estimated jointly with the value equations were quite similar which is the expected result because there is no sample bias in the probit equation. The basic insights from the four simple probits are discussed briefly before preceding to the joint estimation results.

Taken together, the results of these four probit models[14] are intuitively pleasing and support the agency/competitive information scenario hypothesized in the first part of section two. Agency issues arise because managers are compensated on a percentage-of-assets-managed basis. Ceteris paribus, it is in the best interest of managers to

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[14]The individual probit results have been reviewed by a referee of this *Journal* and are available on request from the authors.

sell the smaller (coefficient on net square feet negative), less accessible (coefficient on distance to highway positive) properties that were less cost efficient to manage than larger, more easily accessible properties.

It is also in managers' best interests to sell properties in markets with a well-known high demand for constructed space (coefficient on change in per capita income positive) during a less-well-known "over production" to meet that demand (coefficients on changes in both construction earnings and finance, insurance and real estate earnings negative signaling an end to the building boom). In this analysis, the use of government statistics that were available to the public only well after the transaction dates proxy for the primary local market research efforts of sophisticated investors. Increases in demand are more easily documented (better known) than increases in available supply because preleasing activity (leasing during construction) in large part determines the amount of new available supply. While this preleasing information is not openly shared, it is "more available" to large institutional investors who are actively involved in the market for tenants. Such sales should produce superior appreciation return performance, which would, in turn, be expected to attract more pension fund assets to those managers achieving this superior performance. The detailed probit results suggest that managers did, indeed, act in such a fashion, and support a conclusion that the managers were sophisticated investors tending to sell during the surge in supply but before that increased supply "hit the market" and drove down prices.

## JOINT ESTIMATION RESULTS

Tables 2 through 5 present results from the joint estimation of the probit and pricing equations. The probit equation specifications are identical to those explained in the previous section. The pricing specifications were arrived at using the theoretical justifications set forth in the second part of section two. Preliminary OLS regressions were then performed, and all variables with $t$-statistics greater than 1 in absolute value were retained as the final specifications. The probit and pricing equations were then reestimated by the joint maximum likelihood procedure.

The parameter estimates for the probit results are generally unchanged. This is the expected result because the probit equation does not suffer from sample selectivity so all that is gained through joint estimation for this equation is increased efficiency. However, typically there is some drop in statistical significance—an indication that the asymptotic efficiency of the joint estimator has not come into play at the relatively small sample sizes available for this study.

**TABLE 2**

**Office Properties**

Joint Estimation Sampling Weights:

| | |
|---|---|
| Sold: | 0.276 |
| Unsold: | 1.955 |

Maximum Likelihood Estimates of Selection Model

| | |
|---|---|
| Number of Observations | 98 |
| Log-Likelihood | −239.72 |

Probit Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | −5.47334 | 2.612 |
| Net Sq. Ft. | −0.00490741 | 0.004759 |
| Holding Period | −0.0144991 | 0.01062 |
| Labor Unemp. Rate | 47.8187 | 22.03 |
| Changes in Inc. PC | 113.689 | 37.86 |
| Change in Fire Earn. | −9.01683 | 10.53 |

Number of Observations 54

Hedonic Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | 279.278 | 70.66 |
| Income Per Sq. Ft. | 33.4114 | 3.589 |
| Cap. Rate | −144.686 | 38.97 |
| Holding Period | −0.321228 | 0.1087 |
| Cap. Imp./Sq. Ft. | 10.9440 | 3.439 |
| # of Stories | 2.60412 | 0.6741 |
| Maj. Credit Ten. | 14.8476 | 5.546 |
| Bond Proxy | −12.8610 | 6.673 |
| Change in Pop. | 680.093 | 225.9 |
| *Sigma* | 13.3314 | 1.939 |
| *Rho* | −0.592069 | 0.4620 |

Of most interest are the estimates of *rho*, the coefficient of correlation between the error terms of the probit and pricing equations. If this coefficient is significant, then the maximum likelihood estimators for the pricing equations may only be obtained by way of this joint estimation procedure. However, if the correlation coefficient is not significant, then ordinary least squares will produce maximum likelihood estimates of the pricing equation. For three of the property types in this sample, *rho* is statistically insignificant, indicating that ordinary least squares estimates of the pricing function will produce statistically correct estimates of the parametric coefficients. However, for the retail subsample *rho* is negative and significant at the 5% level. Thus, for this subsample, OLS estimates of the price equation are biased and inconsistent.

Table 6 presents the OLS estimated pricing functions for the retail

## TABLE 3

### Retail Properties

Joint Estimation Sampling Weights:

| | |
|---|---|
| Sold: | 0.471 |
| Unsold: | 2.095 |

Maximum Likelihood Estimates of Selection Model

| | |
|---|---|
| Number of Observations | 87 |
| Log-Likelihood | -173.59 |

Probit Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | -1.81878 | 2.805 |
| Maj. Credit Ten. | 2.93735 | 1.499 |
| Const. Earn. | 3.57456 | 1.779 |
| Income PC | -0.563060 | 0.3055 |
| Changes in Const. E. | -26.2933 | 9.474 |
| Change In Inc. PC | 196.848 | 68.88 |
| Dist. to Hiway | 0.924215 | 0.4512 |
| Holding Period | -0.0110155 | 0.01386 |

Number of Observations 58

Hedonic Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | 49.5697 | 17.18 |
| Income Per Sq. Ft. | 39.2868 | 1.985 |
| Low Inc. Penalty | -16.0135 | 5.838 |
| Cap. Rate | -26.2102 | 7.658 |
| Cap. Imp./Sq. Ft. | 3.03674 | 1.034 |
| Holding Period | -0.0565530 | 0.03908 |
| % Pass Thru | -0.0883716 | 0.04224 |
| Income PC | 0.614854 | 0.2494 |
| Change in Pop. | 209.140 | 42.46 |
| *Sigma* | 3.74749 | 0.4764 |
| *Rho* | -0.870060 | 0.3629 |

subsample. Although the signs of all coefficients are the same as shown in Table 3, both the magnitudes and the standard errors are quite different. Table 7 presents return series generated from each model. These series are similar, though far from identical. Thus, at least for this sample, the joint estimation had a small effect on the estimated return series. Because this result is probably due in large part to the rather complete specifications of the pricing models, this result may not be generalizable to other samples. If other pricing models are to be used to generate asset class returns, then this same joint estimation procedure should be used to test and correct for the presence of sample selectivity bias.

**TABLE 4**

**Industrial Warehouse Properties**

Joint Estimation Sampling Weights:

| | |
|---|---|
| Sold: | 0.397 |
| Unsold: | 1.905 |

Maximum Likelihood Estimates of Selection Model

| | |
|---|---|
| Number of Observations | 178 |
| Log-Likelihood | −407.00 |

Probit Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | −5.67277 | 1.312 |
| Net Sq. Ft. | −0.00170369 | 0.002076 |
| Dist. to Hiway | 0.979392 | 0.3415 |
| Major Cr. Ten. | 0.454589 | 0.3488 |
| Holding Period | −0.0108441 | 0.004975 |
| Labor Unemp. Rate | 32.0002 | 10.07 |
| Change in Inc. PC | 89.2888 | 15.80 |
| Change in Con. Earn. | −10.8351 | 4.014 |

Number of Observations 102

Hedonic Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | 2.01926 | 6.799 |
| Income/Sq. Ft. | 16.2196 | 4.287 |
| Low Inc. Penalty | −8.65338 | 2.802 |
| Hi. Inc. Adj. | 6.96414 | 6.665 |
| # of Buildings | 2.48516 | 0.9563 |
| Age | −0.448212 | 0.1774 |
| Free Standing | 9.60558 | 3.853 |
| Income PC | 1.04741 | 0.3721 |
| Minor Cr. Ten | −4.51721 | 1.729 |
| *Sigma* | 7.40471 | 0.5410 |
| *Rho* | 0.249419 | 0.4108 |

## CONCLUSIONS

As demonstrated by the analysis in section five, there is a clear bias in those properties sold from the FRC Index. Managers tended to sell (i) those properties that were least rewarding from the perspective of investment manager compensation, and (ii) those properties located in markets with strong current demand but rapid recent increases in new supply that were not continuing. The probit analysis did not provide a perfect prediction of sale in any case but, in all cases, identified independent variables and overall predictive equations that were highly significant. Because the FRC Property Index is the standard for measuring commercial real estate returns, this has clear implications for ongoing investment research. If a subset of all properties (a group

## TABLE 5

## Industrial—R&D

**Joint Estimation Sampling Weights:**

| | |
|---|---|
| Sold: | 0.409 |
| Unsold: | 1.606 |

*Maximum Likelihood Estimates of Selection Model*

| | |
|---|---|
| Number of Observations | 71 |
| Log-Likelihood | −134.03 |

Probit Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | −2.60776 | 1.818 |
| % Office | −2.06916 | 1.548 |
| Manu. Earn. | −0.322354 | 0.3232 |
| Wholsale Earn. | 0.964584 | 0.9947 |
| Changes in Inc. PC | 136.042 | 57.34 |
| Change in Lab. U.R. | −4.89588 | 4.024 |
| Change in Con. E. | −30.6639 | 11.78 |
| Changes in Man. E. | -19.3443 | 15.76 |

Number of Observations 35

Hedonic Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | −23.6231 | 13.66 |
| Income Per/Sq. Ft. | 36.5235 | 3.276 |
| Low Inc. Penalty | −28.7366 | 4.247 |
| Lease Maturity | −1.00332 | 0.4726 |
| Income PC | 1.98423 | 0.5951 |
| Change in S.E. | 217.026 | 75.13 |
| Wholesale Earn. | -9.71691 | 2.807 |
| *Sigma* | 6.77968 | 1.026 |
| *Rho* | 0.306739 | 0.7095 |

## TABLE 6

## Retail Properties

OLS Estimates

Number of Observations 58
Adjusted $R^2$ = .94

| Variable | Coefficient | Std. Error |
|---|---|---|
| Constant | 43.8182 | 14.58 |
| Income S.F. | 38.9104 | 1.809 |
| Low Inc. Pen. | -16.5494 | 4.966 |
| Cap. Rate | -23.5605 | 7.078 |
| Cap. Imp./Sq. Ft. | 2.97034 | 0.8945 |
| Holding Period | −0.0604249 | 0.3078 |
| % Pass Thru | −0.0697873 | 0.2823 |
| Income P.C. | 0.576702 | 0.2286 |
| Change in Pop. | 207.580 | 35.57 |

## TABLE 7

### Retail Property Returns
### OLS v. Joint Estimation Results

| | OLS Equally Weighted | | | Joint Estimation Equally Weighted | | |
|---|---|---|---|---|---|---|
| Yr. Q | Total | Income | Apprec. | Total | Income | Apprec. |
| 821 | 0.05012 | 0.0220261 | 0.02809 | 0:05452 | 0.0219208 | 0.03260 |
| 822 | −0.01677 | 0.0220376 | −0.03881 | −0.02124 | 0.0218636 | −0.04310 |
| 823 | 0.06964 | 0.0230837 | 0.04656 | 0.07420 | 0.0230181 | 0.05119 |
| 824 | −0.01626 | 0.0230353 | −0.03930 | −0.02307 | 0.0228544 | −0.04592 |
| 831 | 0.02997 | 0.0248226 | 0.00514 | 0.02971 | 0.0248118 | 0.00490 |
| 832 | 0.06860 | 0.0244818 | 0.04412 | 0.07403 | 0.0244924 | 0.04953 |
| 833 | 0.10907 | 0.0235662 | 0.08551 | 0.11679 | 0.0234522 | 0.09334 |
| 834 | 0.03109 | 0.0213464 | 0.00974 | 0.03225 | 0.0210998 | 0.01115 |
| 841 | 0.06255 | 0.0209882 | 0.04156 | 0.06786 | 0.0207206 | 0.04714 |
| 842 | −0.06399 | 0.0195760 | −0.08357 | −0.07043 | 0.019210 | −0.08968 |
| 843 | 0.07651 | 0.0207426 | 0.05576 | 0.08390 | 0.0205830 | 0.06332 |
| 844 | −0.00671 | 0.0186566 | −0.02537 | −0.00773 | 0.0184450 | −0.02618 |
| 851 | 0.04972 | 0.0189168 | 0.03080 | 0.05354 | 0.0187574 | 0.03478 |
| 852 | −0.04202 | 0.0190890 | −0.06111 | −0.04988 | 0.0188321 | −0.06871 |
| 853 | 0.05759 | 0.0205267 | 0.03707 | 0.06017 | 0.0204503 | 0.03972 |
| 854 | 0.07878 | 0.0200977 | 0.05868 | 0.08276 | 0.0199655 | 0.06279 |
| 861 | 0.00794 | 0.0192341 | −0.01130 | 0.00776 | 0.0190031 | −0.01125 |
| 862 | −0.00300 | 0.0194679 | −0.02247 | −0.00555 | 0.0192174 | −0.02476 |
| 863 | 0.09706 | 0.0202910 | 0.07677 | 0.10249 | 0.0200268 | 0.08247 |
| 864 | 0.01776 | 0.0182274 | −0.00047 | 0.01933 | 0.0178859 | 0.00145 |
| | Value Weighted | | | Value Weighted | | |
| Yr. Q | Total | Income | Apprec. | Total | Income | Apprec. |
| 821 | 0.04168 | 0.021316 | 0.02036 | 0.04585 | 0.021145 | 0.02471 |
| 822 | −0.02219 | 0.021624 | −0.04381 | −0.02638 | 0.021385 | −0.04776 |
| 823 | 0.08362 | 0.023584 | 0.06003 | 0.08703 | 0.023420 | 0.06361 |
| 824 | −0.01297 | 0.023347 | −0.03632 | −0.01952 | 0.023108 | −0.04263 |
| 831 | 0.07323 | 0.026214 | 0.04702 | 0.07303 | 0.026117 | 0.04691 |
| 832 | 0.07447 | 0.025037 | 0.04944 | 0.07900 | 0.024948 | 0.05406 |
| 833 | 0.05774 | 0.022347 | 0.03539 | 0.06499 | 0.022209 | 0.04278 |
| 834 | 0.05153 | 0.021783 | 0.02975 | 0.05238 | 0.021495 | 0.03088 |
| 841 | 0.05912 | 0.021081 | 0.03803 | 0.06355 | 0.020283 | 0.04277 |
| 842 | −0.06785 | 0.018888 | −0.08674 | −0.07275 | 0.018538 | −0.09129 |
| 843 | 0.08012 | 0.021134 | 0.05899 | 0.08484 | 0.020848 | 0.06399 |
| 844 | −0.01393 | 0.018875 | −0.03281 | −0.01457 | 0.018534 | −0.03310 |
| 851 | 0.02401 | 0.018824 | 0.00518 | 0.02745 | 0.018493 | 0.00896 |
| 852 | −0.03194 | 0.019703 | −0.05164 | −0.03910 | 0.019289 | −0.05839 |
| 853 | 0.04418 | 0.020591 | 0.02359 | 0.04640 | 0.020305 | 0.02609 |
| 854 | 0.06342 | 0.020220 | 0.04320 | 0.06700 | 0.019893 | 0.04711 |
| 861 | 0.00798 | 0.019490 | −0.01151 | 0.00771 | 0.019107 | −0.01140 |
| 862 | −0.00268 | 0.019730 | −0.02241 | −0.00485 | 0.019345 | −0.02419 |
| 863 | 0.07064 | 0.020041 | 0.05060 | 0.07593 | 0.019691 | 0.05624 |
| 864 | 0.01055 | 0.018510 | −0.00796 | 0.01136 | 0.018095 | −0.00674 |

that has sold) is the proxy for the commercial real estate asset class (as it must be in a heterogeneous market), then researchers must be certain that those properties sold are, indeed, "representative" of the asset class.

The results of the weighted probit analysis confirm several of the often cited rationales for recent divestitures by portfolio managers (section two). More importantly from an academic perspective, analyses in the previous section demonstrate that any attempt to measure appreciation return performance from property sales rather than from appraisals must involve a joint estimation of both sales price and probability of sale in order to control for sample selectivity. This result calls into question previous work in this field that has used a sold property data set without adjustment for this bias. While the use of actual sales prices has clear advantages over the use of appraised values [Hoag 1980; Hartzell 1986], the results presented here demonstrate that corrections for sample selectivity bias may be warranted.

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