Exploiting Property Characteristics in Commercial Real Estate Portfolio Allocation*

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Abstract

A parametric portfolio approach is used to estimate optimal commercial real estate portfolio policies. We do so by relying on the NCREIF data set of commercial properties over the sample period 1984:Q2 to 2009:Q1. The richness of this extensive data set and the flexibility of the parametric portfolio approach allow us to consider: (i) a large cross-section of individual properties across various regions and property types; (ii) several property-specific conditioning variables such as cap rates, values, and vacancy rates; and (iii) various macro-economic factors. Property-specific conditioning information is found to be economically important even for portfolios that are well-diversified across geographical regions.

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Commercial real estate is an important asset class. Current estimates put the value of investment grade commercial properties in the U.S. at approximately $3 trillion. Direct investment in commercial real estate by pension funds is significant and is expected to increase in the upcoming years. Despite its growing importance, many questions still remain unexplored in the management of commercial real estate portfolios. For example, how should investors allocate their wealth across different commercial properties? How do the risk-return profiles of property types — apartments, industrial properties, offices, and retail properties — differ from one another? How should investors alter the composition of their commercial real estate portfolios to take advantage of movements in expected returns due to changing underlying macro-economic conditions?

Answers to these questions have been hampered by a variety of factors including both data inadequacies and methodological difficulties. First, previous research on commercial property portfolio management has relied predominantly on aggregate property indices and so cannot provide insights into portfolio allocation at a disaggregated level. Secondly, property returns are typically based on appraisal values. Because appraisals are updated infrequently, they tend to lag market values and render the resultant return series excessively smooth. The moments of these smoothed returns will systematically differ from the moments of the true market returns thereby potentially misallocating commercial real estate portfolios. Finally, recent evidence suggests that property-specific characteristics are related to the moments of commercial property returns. For example, Plazzi, Torous, and Valkanov [2010] provide empirical evidence consistent with a property's cap rate being informative about its subsequent returns.[1] Incorporating property-specific characteristics has the potential to improve the performance of commercial real estate portfolios. Unfortunately, the traditional mean-variance approach would require explicitly modeling the expected returns, variances and covariances of all properties as functions of these characteristics. This task becomes computationally burdensome as the number of properties in the portfolio increases.

In this paper, we apply recent advances in portfolio management (Brandt, Santa-Clara, and Valkanov [2009]) to efficiently incorporate the information contained in property-specific conditioning variables to the allocation of commercial real estate portfolios. In particular, we investigate whether a property's cap rate and other property-specific characteristics provide information that improves property portfolio performance. We do so by parameterizing the portfolio weight of each individual property as a function of its specific characteristics. The fact that a single function of characteristics applies to all properties over time significantly reduces the

[1] Similarly, **?** show that the rent-price ratio reliably forecasts residential property returns.

computational requirements of portfolio management. The coefficients of this portfolio policy are estimated by maximizing the average utility of a typical real estate investor. The Brandt, Santa-Clara, and Valkanov [2009] approach also allows us to to easily impose non-negative weights on the property holdings. Unlike common stocks, it is at present difficult to take short positions in commercial properties because corresponding derivative markets are either nonexistent or are very illiquid.

To estimate the optimal portfolio policy function, we rely on a large cross-sectional database of information on individual properties compiled by NCREIF (National Council of Real Estate Investment Fiduciaries). NCREIF assets are institutional grade commercial properties managed by investment fiduciaries on behalf of tax-exempt pension funds. Current NCREIF properties valuation is approximately $240 billion.[2] The disaggregated NCREIF data allows us to construct "pseudo-market" prices of NCREIF properties using the hedonic-type model of Fisher, Geltner, and Pollakowski [2007]. Intuitively, we rely on the fitted relation between available transaction prices and their corresponding lagged appraisal values and other variables to predict the prices at which properties which were only appraised would have sold for. Total returns based on these prices appear to mimic the time-series behavior of market-based returns. For example, the first-order autocorrelation coefficients of these returns are much lower in absolute value than those of returns based on appraisals.

Along with a property's cap rate, we rely on a number of additional building-specific conditioning variables to characterize a property's portfolio weight. These include a property's size measured by its appraisal value and a property's vacancy rate. Size plays an important role in the return performance of common stocks as well as properties (Pai and Geltner [2007]). Vacancy rates are related to residential property returns (Wheaton [1990]) and we explore their importance for commercial real estate returns. We also consider whether a property is located in a larger and more liquid commercial property market — New York, Washington D.C., San Francisco, Los Angeles, Chicago, and Boston.

Our empirical results are consistent with these property-specific conditioning variables playing an economically as well as statistically significant role in the allocation of commercial real estate portfolios. In particular, we find that the optimal portfolio places more weight, relative to market cap weights, on properties having high cap rates, high leverage ratios, as well as low vacancy rates, and on smaller buildings as measured by their appraisal values. The nature of the optimal

[2] NCREIF aggregates the confidential information contributed by its members and provides indices based on aggregate data, such as the quarterly NCREIF Property Index (NPI), for use by the real estate industry.

portfolio varies systematically across property types. The portfolio allocation of apartments and retail properties can be improved by relying more on cap rates and leverage ratios, while vacancy rates and size appear to be more informative for the allocation of office and industrial property portfolios. Optimal portfolios also vary over economic expansions versus economic recessions. For example, in recessions, optimal portfolios are aggressively tilted towards highly leveraged properties reflecting these properties' strong cash flows.

The plan of this paper is as follows. We begin by discussing the data relied upon in our empirical analysis. The two-step procedure used to estimate the predicted prices of all individual properties in the NCREIF database is detailed. The property characteristics capturing variation in commercial real estate's opportunity set are also introduced. We next briefly review the Brandt, Santa-Clara, and Valkanov [2009] methodology emphasizing how it can be adapted to incorporate changing underlying economic conditions known to be important to the performance of commercial real estate and to impose a no short sales constraint which is necessary when dealing with commercial properties. We then discuss our results both for a portfolio of all NCREIF properties as well as building type specific portfolios. We conclude with a summary of our results.

DATA

We rely on the disaggregated information compiled by NCREIF. This information includes, among other items, a property's location and type, its net operating income and any capital expenditures, as well as the property's price. If a property is sold during a quarter, NCREIF records the net price (net of transaction costs) at which the property sold. Otherwise, NCREIF reports an appraisal value calculated either by an in-house expert (internal appraisal) or by an independent appraiser (external appraisal). Our sample begins in 1984:Q2 and ends at 2009:Q1.

The first step in our analysis is to construct a total return series for each individual property in the NCREIF database. This task is complicated by the fact that NCREIF properties, like other properties, do not transact frequently. For example, out of a total of 174,440 price observations in our NCREIF sample, only 4,889 — about 3% — represent actual sales transactions. These appraisal values, however, are subject to a temporal lag bias as they tend to lag in time true contemporaneous market values. This, in turn, will smoothen periodic returns based on appraisal values. Consequently, the moments of these smoothed returns will systematically differ from the moments of the true market returns. For example, the volatility of returns based on appraisals will be biased downward. Similarly, estimates of the correlations between returns and any conditioning variable will also be biased.[3] In sum, by relying on appraisal returns, the joint structure of returns would be improperly measured thus potentially misallocating commercial real estate in a portfolio context.

Ideally, a portfolio analysis of commercial real estate would make use of transaction prices for a large number of properties over a sufficiently long period of time. To approximate this ideal, we rely on the hedonic regression model of Fisher, Geltner, and Pollakowski [2007] (FGP henceforth) to *estimate* market-based prices of every individual property followed by NCREIF.

We do so by using a two-stage procedure. In the first stage, all transactions in the NCREIF database are used to estimate a hedonic price model in which corresponding transaction prices are regressed against properties' lagged appraisal values as well as several dummy variables controlling for time, property type, and location.[4] The key insight here is that while an appraisal value may represent a noisy estimate of a property's true market value, it serves as a valuable hedonic summarizing a building's characteristics which are either observable, such as its size, or are unobservable, such as its quality. The estimated coefficients from this regression are then used in a second stage to construct predicted, or "pseudo-market", prices based on the appraisal values of those properties that did not transact in a given quarter.[5]

FGP follow a similar procedure in constructing the TBI (Transaction Based Index), an aggregate price index of commercial real estate based on the NCREIF data. However, to construct the TBI, FGP apply their first-stage estimates to a representative property mirroring the average characteristics of a NCREIF property. We, instead, determine the predicted prices for each individual property in the NCREIF database.

Using these predicted prices, denoted by $P_{i,t}$, we calculate the log (total) return for property i in quarter $t+1$ as:

$$r_{i,t+1} = \ln\left(\frac{P_{i,t+1} + NOI_{i,t+1} - CAPX_{i,t+1}}{P_{i,t}}\right) \tag{1}$$

where $NOI_{i,t+1}$ denotes the building's net operating income (income minus operating expenses)

[3] See Geltner [1991] and [1993] for an analysis of the effects of the appraisal procedure on aggregate indices and individual properties.

[4] Property type specific results, when reported, are based solely on data specific to the particular property type. Also, because there are fewer than fifty transactions per quarter in the NCREIF database until the mid-90s, we follow Fisher, Geltner, and Pollakowski [2007] and use only data beginning in 1994:Q2 when estimating property specific returns to minimize their estimation error.

[5] The methodology also accounts for transaction sample selection bias in the first stage using a Heckman (1979) two-step approach. Moreover, a Bayesian noise filtering technique is applied to reduce the effect of noise in the quarterly series due to the limited number of transactions. See Fisher, Geltner, and Pollakowski [2007] for further details on this estimation procedure.

earned during the period $[t; t+1]$ while $CAPX_{i,t+1}$ represents corresponding capital expenditures.[6]

Given these predicted individual property returns, our empirical methodology investigates whether a portfolio allocation across commercial real estate can be improved by relying on conditioning variables. In order to be relevant, these variables must capture variation, either cross-sectional or time-series, in commercial real estate's investment opportunity set. Guided by economic theory, evidence from previous studies, as well as data availability, we select the following conditioning variables:

Cap rate. A property's capitalization rate is calculated as the ratio between its Net Operating Income (NOI) and its predicted value, $cap_t = NOI_{i,t}/P_{i,t}$. A cap rate corresponds to a stock's dividend-price ratio. There is ample evidence in the finance literature consistent with a stock's dividend-price ratio predicting subsequent stock returns. Similarly, Plazzi, Torous, and Valkanov [2010] document that a property's cap rate predicts subsequent property returns.

Size. We also include size as measured by a property's appraised value. The size effect is a prominent feature of common stock performance with small stocks, as measured by their market capitalization, earning a sizable return premium. However, Pai and Geltner [2007] investigate the size effect in the context of the institutional commercial real estate market and find that larger, as opposed to smaller properties, earn a return premium.

Vacancy rate. Vacancy rates are the final property characteristic that we rely on. Vacancy rates proxy for the supply versus demand relation prevailing in commercial real estate markets. As such, vacancy rates may capture changes in the commercial real estate opportunity set and so subsequent property expected returns. Wheaton [1990] provides a theoretical argument why vacancies and residential real estate values are negatively related at least contemporaneously. Empirically, Frew and Jud [1988] find vacancy rates to be a key factor in the determination of commercial office rents, while Smith [1974] directly links local geographic and economic conditions to vacancy rates.

A series of filters are subsequently applied to ensure that our results are not driven by outliers which may reflect data entry and other errors.[7] In the end, we are left with a total of 52,569 property-quarters returns starting in 1984:Q2 and ending in 2009:Q1, of which 1,383 correspond to actual transactions. This pooled data serves as the basis of our estimation efforts.

[6] When a property transacts, the predicted price during that quarter is set equal to the transaction price.

[7] In order to ensure that our results are not affected by outliers, a number of filters are applied. First, we drop observations for which the ratio between NOI and current price exceeds 0.2 in absolute value. This is done to eliminate cases where the NOI is too large in negative or positive terms relative to the price of the building. We also drop returns larger than 0.8 or smaller than -0.4. These represent less than the 0.5% of the overall number of observations.

Summary Statistics

Summary statistics of the predicted returns, conditioning variables and other related series are provided in Exhibit 1.

Given the returns of individual properties, we construct a number of representative property portfolios. To do so, we aggregate our individual property returns on a value-weighted basis, where an individual property's portfolio weight is given by its appraised value. The return to this market capitalization portfolio of all NCREIF properties is denoted by r. We also consider portfolios based on a particular property type – apartment (apt), industrial properties (ind), office properties (off), and retail (rtl) – and denote the corresponding portfolio returns by r_{apt}, r_{ind}, r_{off}, and r_{rtl}, respectively.

Means and standard deviations, both time-series and cross-sectional, as well as first-order autocorrelation coefficients of the various returns series are tabulated in Panel A. Average returns are comparable across property types though industrial property returns are on average slightly higher and more variable. Office property returns have the highest cross-sectional variability. Notice that the autocorrelation of the returns series is quite low (in absolute value) across the property types. This is consistent with the time-series behavior of market-based returns.

All of the conditioning variables are persistent over time. Vacancy rates and size are particularly sticky. To the extent that these variables provide valuable information about the moments of property returns, it appears that this information does not quickly dissipate.

We are also interested in understanding how commercial real estate investment opportunities vary with economic conditions. To measure time variation in underlying economic conditions, we rely on the Chicago Fed National Activity Index (CFNAI), a monthly coincident indicator of broad-based economic activity originated by Stock and Watson (1999).[8] A positive value of CFNAI corresponds to a macro-economic expansion while a macro-economic contraction coincides with a negative CFNAI value. As can be seen from Exhibit 1, CFNAI is also persistent.

We now turn our attention to the time-series correlations amongst these series. From Panel B of Exhibit 1, apartment returns are seen to be virtually uncorrelated with industrial and retail property returns while industrial and retail property returns are themselves highly correlated. All returns are negatively correlated with the size of the corresponding property measured by its appraised

[8]This index is based on the first principal component of eighty-five economic activity series and is constructed to have an average value of zero and a standard deviation of one. Because economic activity tends to grow at a trend, an index reading of zero corresponds to the economy growing at trend.

value while all returns and cap rates are positively correlated. We see no correlation between vacancy rates and returns. Finally, a positive correlation prevails between returns and our measure of aggregate economic activity.

METHODOLOGY

We parameterize portfolio weights directly as a function of property characteristics. For each quarter t, there are a large number N_t of commercial properties in the NCREIF property universe. At the beginning of our sample, N_t is 116, and reaches a maximum of 2577 in later quarters. For each property, we have its return $r_{i,t+1}$ and a set of corresponding property characteristics collected in a k-dimensional vector $x_{i,t}$. An investor's problem is to allocate a portfolio across the N_t properties using the information contained in $x_{i,t}$.[9]

The fraction of wealth invested in property i at time t is denoted by $w_{i,t}$. The investor chooses portfolio weights to maximize the conditional expected utility of the resultant property portfolio return $r_{p,t+1}$:

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t \left[u \left(r_{p,t+1} \right) \right] \tag{2}$$

where $r_{p,t+1} = \sum_{i=1}^{N_{t+1}} w_{i,t} r_{i,t+1}$ and u denotes a pre-specified utility function.

Basic Case

In the basic case, we parameterize portfolio weights as a linear function of the property characteristics

$$w_{i,t} = \overline{w}_{i,t} + \frac{1}{N_t} \delta' x_{i,t} \tag{3}$$

where $\overline{w}_{i,t}$ are benchmark weights and δ is a k-dimensional vector of parameters to be estimated.

The vector $x_{i,t}$ is normalized to have a zero cross-sectional mean and a variance of unity. This implies that the second term in expression (3) sums to zero across properties at time t and thus captures deviations from the benchmark weights. This allows the portfolio allocation to be tilted

[9] The decision of how much to allocate to commercial real estate relative to other asset classes, such as stocks and bonds, is assumed to have already been made.

either towards or away from $\overline{w}_{i,t}$. The tilting is done according to the conditioning information contained in $x_{i,t}$.

We choose $\overline{w}_{i,t}$ to be market capitalization weights. That is, our benchmark is a portfolio of all NCREIF properties which invests in each available property in proportion to its current appraised value. However, any other benchmark can be used. For example, we can assess whether conditioning information can improve a portfolio manager's commercial real estate allocation by choosing $\overline{w}_{i,t}$ to be the manager's current portfolio weights.

Given estimates of δ, the weights associated with the optimal portfolio policy are fully observable. It is important to note that δ is constant across time and across properties. Rebalancing of the portfolio away from the benchmark $\overline{w}_{i,t}$ is only due to the characteristics $x_{i,t}$ differing across properties and across time.

We maximize the sample analogue of expression (2) with respect to the unknown parameters δ to estimate the optimal portfolio weights:

$$\max_{\delta} \frac{1}{T} \sum_{t=1}^{T} u \left(\sum_{i=1}^{N_{t+1}} \left(\overline{w}_{i,t} + \frac{1}{N_t} \delta' x_{i,t} \right) .r_{i,t+1} \right) \tag{4}$$

This problem is simple to optimize. A large and changing number of properties across time as well as a large number of conditioning variables can be accommodated.

Macro-Economic Variation

In the basic case above, the coefficients of the portfolio policy δ are constant through time. This implies that the relation between property characteristics and the distribution of property returns is time invariant. However, this simplifying assumption may not be realistic in the case of commercial real estate whose performance is closely related to business cycle movements in the underlying economy.

To allow for the possible time variation in the coefficients of the portfolio policy, we follow Brandt, Santa-Clara, and Valkanov [2009] and explicitly model the coefficients as functions of a business cycle variable z_t. In this case, the portfolio policy (3) is extended as

$$w_{i,t} = \overline{w}_{i,t} + \frac{1}{N_t} \delta' \left(z_t \otimes x_{i,t} \right) \tag{5}$$

where $\otimes$ denotes the Kronecker product of two vectors. Now the impact of property characteristics on the property portfolio weights varies with the realization of the business cycle variable z_t. In our application, business cycle variation in economic conditions will be captured by either the coincident indicator CFNAI or the relative Treasury bill rate *r-tbill*.

No Short Sales Constraint

The portfolio policies considered to this point do not constrain the portfolio weights. As a consequence, for some properties the weights may turn out to be negative and require the properties to be shorted. While shorting is common in the case of stocks, it is not feasible for properties. Therefore, we need to modify a portfolio policy to directly impose the constraint that portfolio weights are non-negative.

There are a number of alternative ways of imposing non-negative portfolio weights. For example, we can optimize expression (3) for values of δ such that the constraint $w_{i,t} \geq 0$ is satisfied for all i's and all t's. This approach is computationally burdensome. Rather, we impose non-negativity as follows

$$w_{i,t}^{+} = \frac{\max\left[0, w_{i,t}\right]}{\sum_{i=1}^{N_{t+1}} \max\left[0, w_{i,t}\right]}. \qquad (6)$$

This approach is straightforward to implement and interpret. However, unlike the previous two specifications, it is non-linear in the conditioning variables.

RESULTS

Exhibit 2 displays the optimal portfolio results for our basic specification (3) and imposing the non-negativity constraint (6) when estimated using all NCREIF properties. Here and throughout, we assume that the investor has power utility with a coefficient of relative risk aversion equal to five.[10] The results for the benchmark NCREIF market cap weights are displayed in column I, while in subsequent columns, we sequentially add each of the cap rate and the other posited control variables. As in standard regression analysis, a coefficient can be interpreted as the marginal effect of a particular variable $x_{i,t}$ on the optimal portfolio policy function. Moreover, since the conditioning variables are standardized, the coefficients are directly comparable both within as well as across specifications with a higher absolute value indicative of a variable having a greater

[10]Defined as $u\left(W\right) = \frac{W^{1-\gamma}}{1-\gamma}$ where γ is the coefficient of relative risk aversion.

effect in the portfolio policy.

Consistent with economic intuition, all else being equal, the optimal portfolio places more weight, relative to the market cap weights, on properties with high cap rates, low vacancy rates, and large buildings as measured by their appraised value (Columns II-IV). Being located in a larger and more liquid Top 6 property market is by itself statistically insignificant but the size effect is significantly enhanced within such markets (Column V). We also include location dummies in the final specification (Column VI) and see that none are statistically significant. This implies that the portfolio of all NCREIF properties weighted by their appraised values is well diversified by location across the country. The benefits of holding the optimal portfolio are evident in the Sharpe ratio's increase from less than 0.5 in the case of the benchmark portfolio to nearly .7 for the optimal portfolio. Importantly, with a relative risk aversion of five, we see a large gain in the certainty equivalent return[11] as a result of investing in the optimal portfolio relative to holding the benchmark.

Property characteristics are also important in explaining deviations of optimal portfolio weights from market capitalization weights when investment is restricted solely to a particular property type. These results are tabulated in Exhibit 3 along with the corresponding property type specific benchmark market cap portfolios. For all property types, the optimal portfolios are tilted towards high cap rate properties. This cap rate effect is strongest for apartments and retail properties. In addition, the optimal office and industrial property portfolios are very sensitive to vacancy rates with relatively more wealth invested in low vacancy rate buildings. From Exhibit 3 we also see that the optimal apartment and industrial property portfolios are tilted towards large properties especially in the Top 6 property markets. By contrast, this size effect is present only for office properties located in the Top 6 property markets but is diminished for retail properties located in the Top 6 property markets. The benefits of holding the optimal property specific portfolios are also evident across all property types, but especially for apartments and offices. In the case of apartments, investing in the optimal portfolio relative to holding the benchmark increases the Sharpe ratio from approximately .8 to approximately 1.4. Similarly, investing in the optimal office portfolio relative to holding its benchmark increases the Sharpe ratio from approximately 1 to approximately 1.4.

The differences in the estimated coefficients across property types evident in Exhibit 3 are consistent with apartments, industrial properties, offices, and retail properties being characterized

[11]The certainty equivalent return is the fixed known return an investor is indifferent in receiving as compared to the uncertain return generated by the portfolio.

by different risk-return profiles. In particular, cap rates are, on average, more important in the case of apartments and retail properties while, on the other hand, for offices and industrial properties vacancy rates and size are, on average, more important.

Exhibit 4 allows the effects of the property characteristics on the optimal portfolio weights, overall and property type specific, to vary with the realization of the coincident indicator CFNAI. By estimating specification (5) this proxy for the business cycle variable z_t allows us to investigate how an investor can time the composition of optimal property portfolios.

Turning our attention first to the results for all NCREIF properties, we see in Exhibit 4 that in expansions, CFNAI > 0, the optimal portfolio is tilted more in the direction of both high cap rate and low vacancy rate properties. In recessions, CFNAI < 0, the optimal portfolio is tilted more in the direction of large properties, especially those located in the Top 6 property markets. This is a counter-cyclical investment policy which in recessions directs investors to seek out more valuable properties with corresponding stronger cash flows.

From Exhibit 4, we that the tilt towards high cap rate properties in expansions is especially evident in industrial, office, and retail properties. The tilt towards low vacancy rate properties in expansions is optimal for all property types. The tilt towards larger properties in recessions is due primarily to office and retail properties. Interestingly, the optimal office portfolio tilts towards smaller properties in expansions. Also, regardless of the property type, optimal portfolio holdings of properties located in the Top 6 property markets are seen to tilt towards large properties in recessions. The previously documented fact that the size effect is diminished in the Top 6 property markets reflects the fact that the optimal retail property portfolio in recessions tilts towards smaller retail properties located in the Top 6 property markets.

CONCLUSIONS

A commercial property is characterized by more than simply being an office building or an industrial warehouse and whether it is located in the U.S. North-East or the U.S. South. Yet heretofore commercial real estate portfolio analytics have relied primarily on property type and property location when allocating investment across commercial properties. Since other property characteristics, for example, property cap rates, are related to the moments of property returns, we apply the parametric portfolio allocation approach of Brandt, Santa-Clara, and Valkanov [2009] to efficiently incorporate this information into commercial real estate portfolio management. Not surprisingly, taking such information into account significantly improves the performance of commercial real estate portfolios relative to property portfolios that are well-diversified across property types and property location.

When considering the universe of all NCREIF properties, the optimal portfolio weights are tilted more towards high cap rate, highly leveraged, and low vacancy rate properties and away from high value properties when compared to a portfolio that holds these properties in proportion to their appraisal values. For building specific portfolios, all of the optimal portfolios are tilted towards highly leveraged portfolios but the optimal office portfolio differs from the other optimal portfolios. In particular, the optimal office portfolio is insensitive to cap rates but extremely sensitive to vacancy rates with relatively more wealth invested in low vacancy rate properties. These portfolio policies, however, are shown to systematically vary with prevailing economic conditions. For example, in recessions, optimal portfolios are aggressively tilted towards highly leveraged properties reflecting these properties' strong cash flows.

While our results are encouraging, they should be extended in several directions. For example, it is important to investigate the sensitivity of our results to including transaction costs or other market frictions. Also, while all of this paper's results are in-sample, it would be interesting to investigate whether the optimal strategy estimated in-sample would yield equally impressive results out-of-sample. We leave investigating these and other issues to future research.

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Exhibit 1: Summary Statistics

Panel A displays the time-series mean, standard deviation, and first-order autoregressive coefficient for: the value-weighted aggregate return series to all properties (all) during the 1984:2-2009:1 period, and separately for apartments (apt), industrial properties (ind), offices (off), retail (rtl) during the 1994:2-2009:1 period; the cap rate, vacancy rate, and size (measured by appraisal value) for the value-weighted avg of all properties; the CFNAI index of economic activity. For each variable but the CNFAI, the table also shows the average cross-sectional standard deviation (Csd). Panel B displays the time-series correlation coefficients during the common (pairwise) sample periods.

Panel A

	all	apt	ind	off	rtl	cap	vac	size	CFNAI
Mean	0.0257	0.0256	0.0327	0.0275	0.0284	0.0184	0.2677	17.6171	-0.0204
Std	0.0665	0.0378	0.0648	0.0360	0.0395	0.0024	0.2741	0.3694	0.6413
AR(1)	-0.3156	0.1434	-0.2933	0.2143	-0.1005	0.8501	0.9831	0.9543	0.7925
Csd	0.0644	0.0515	0.0612	0.0715	0.0609	0.0088	0.2455	1.0866	-

Panel B

	all	apt	ind	off	rtl	cap	vac	size	CFNAI
all	1								
apt	0.288	1							
ind	0.656	0.075	1						
off	0.575	0.315	0.330	1					
rtl	0.715	-0.060	0.528	0.264	1				
cap	0.296	0.314	0.111	0.196	0.052	1			
vac	-0.002	0.115	-0.029	-0.109	0.041	-0.107	1		
size	-0.167	-0.537	-0.148	-0.387	-0.121	-0.395	-0.761	1	
CFNAI	0.205	0.487	0.218	0.406	0.174	0.251	0.246	-0.545	1

Exhibit 2: Portfolio allocation – all types

Optimal portfolio policy coefficients with non–negative weights estimated on all properties spanning the 1984:2-2009:1 period under different specifications: (I) corresponds to the unconditional case; (II) uses cap rates as conditioning variable; (III) to (VI) add progressively leverage, the vacancy rate, size (measured by the appraisal value), the dummy for the six most liquid markets and its interaction with size, and finally location dummies. In the optimization, the risk aversion parameter γ is set to 5. The first set of rows shows the estimated coefficients of the portfolio policy and their associated standard errors. The p-value of the LR test under the null hypothesis that the parameter estimates are jointly equal to zero is also displayed. The second set of rows shows the average absolute portfolio weight, the maximum portfolio weight, the average fraction of zero weights in the portfolio, and the minimum and maximum number of cross-sectional observations. The third set of rows displays, for the optimal portfolio, the average return (, standard deviation, the certainty-equivalent, and the Sharpe ratio. Finally, the intercept, the slope coefficient, and the idiosyncratic volatility of a market model regression are reported. The average risk-free rate is 0.04 (annualized).

	I	II	III	IV	V	VI
θ_{cap}		10.612	5.450	3.952	11.753	9.817
Std.Err.		1.134	1.292	3.429	5.886	7.312
θ_{vac}			-9.169	-11.660	-13.977	-9.083
Std.Err.			1.222	2.995	4.716	3.711
θ_{size}				12.035	6.827	9.098
Std.Err.				3.417	3.216	4.483
θ_{top6}					-1.564	3.326
Std.Err.					0.981	2.120
$\theta_{top6 \times size}$					8.291	6.711
Std.Err.					2.712	2.733
θ_{East}						5.592
Std.Err.						9.069
θ_{West}						6.241
Std.Err.						10.995
$\theta_{MidWest}$						1.408
Std.Err.						9.149
θ_{South}						5.471
Std.Err.						10.416
LR p-value	-	0.000	0.000	0.000	0.000	0.000
$\lvert w_i \rvert \times 100$	0.068	0.068	0.068	0.068	0.068	0.068
$\max\ w_i \times 100$	1.550	0.582	0.831	2.218	2.362	2.477
$\sum I(w_i = 0)/N_t$	0.000	0.055	0.262	0.415	0.360	0.484
$\min\ N_t$	707	707	707	707	707	707
$\max\ N_t$	4518	4518	4518	4518	4518	4518
$\bar{r}$	0.103	0.115	0.124	0.129	0.130	0.130
σ	0.133	0.131	0.135	0.137	0.137	0.138
$CE(r)$	0.058	0.071	0.079	0.082	0.083	0.082
$SR(r)$	0.472	0.567	0.628	0.652	0.659	0.650
α	-	0.003	0.005	0.006	0.006	0.006
β	-	0.986	1.006	1.027	1.027	1.032
$\sigma(\epsilon)$	-	0.010	0.015	0.012	0.011	0.013

Exhibit 3: Portfolio allocation by property type

Optimal portfolio policy coefficients with non–negative weights separately estimated on data for apartments (apt), industrial properties (ind), offices (off), and retail properties (rtl) for the 1994:2-2009:1 period. Variables are defined as in Exhibit 2.

		apt		ind		off		rtl
θ_{cap}	-	19.746	-	4.879	-	13.149	-	10.780
Std.Err.	-	4.179	-	5.156	-	8.151	-	4.791
θ_{vac}	-	-1.212	-	-4.970	-	-9.770	-	-6.482
Std.Err.	-	1.224	-	3.087	-	5.689	-	4.274
θ_{size}	-	0.831	-	4.903	-	-0.214	-	9.199
Std.Err.	-	0.448	-	2.759	-	1.753	-	4.327
$\theta_{top6\times size}$	-	2.842	-	5.759	-	5.398	-	-3.706
Std.Err.	-	0.708	-	2.355	-	2.467	-	1.712
LR p-value	-	0.000	-	0.000	-	0.000	-	0.000
$\lvert w_i \rvert \times 100$	0.272	0.272	0.154	0.154	0.210	0.210	0.291	0.291
$\max\ w_i \times 100$	2.493	3.540	3.650	4.820	2.853	2.527	3.955	4.220
$\sum I(w_i = 0)/N_t$	-	0.272	-	0.464	-	0.259	-	0.305
$\min\ N_t$	203	203	313	313	292	292	167	167
$\max\ N_t$	921	921	1585	1585	1204	1204	778	778
$\bar{r}$	0.103	0.152	0.131	0.155	0.110	0.141	0.114	0.136
σ	0.076	0.082	0.130	0.131	0.072	0.074	0.079	0.083
$CE(r)$	0.088	0.136	0.094	0.117	0.097	0.127	0.100	0.122
$SR(r)$	0.828	1.375	0.700	0.877	0.969	1.359	0.933	1.167
α	-	0.011	-	0.006	-	0.007	-	0.005
β	-	1.052	-	1.007	-	1.019	-	1.015
$\sigma(\epsilon)$	-	0.019	-	0.01	-	0.012	-	0.019

Exhibit 4: Portfolio allocation – interaction with CFNAI, all and individual property types

Optimal portfolio policy coefficients with non–negative weights estimated when the four conditioning variables are interacted with the CFNAI Index. The interaction is performed on a dummy variable which equals one if the index is greater than zero (expansion), and zero otherwise. The corresponding coefficients are denoted, respectively, with a plus and minus sign. Results based on all properties span the 1984:2-2009:1 period while those on individual properties cover the 1994:2-2009:1 period. Variables are defined as in Exhibit 2.

		all		apt		ind		off		rtl
θ_{cap+}	-	8.040	-	26.805	-	10.777	-	12.494	-	25.750
Std.Err.	-	5.417	-	7.369	-	9.284	-	10.365	-	33.465
θ_{cap-}	-	3.379	-	23.313	-	2.609	-	4.156	-	4.507
Std.Err.	-	8.206	-	8.732	-	6.808	-	10.213	-	36.660
θ_{vac+}	-	-14.768	-	-1.086	-	-6.659	-	-8.301	-	-13.688
Std.Err.	-	5.767	-	1.921	-	5.620	-	6.011	-	20.288
θ_{vac-}	-	-3.715	-	-0.674	-	-4.985	-	-5.088	-	-10.617
Std.Err.	-	1.953	-	1.917	-	6.379	-	4.457	-	23.974
θ_{size+}	-	3.007	-	1.368	-	7.280	-	-4.110	-	4.902
Std.Err.	-	2.447	-	0.705	-	5.208	-	2.542	-	8.529
θ_{size-}	-	9.676	-	1.983	-	-1.016	-	4.613	-	32.664
Std.Err.	-	4.668	-	1.320	-	3.682	-	4.968	-	51.003
$\theta_{(top6\times size)+}$	-	3.693	-	0.599	-	0.083	-	1.469	-	-6.730
Std.Err.	-	1.898	-	0.729	-	1.217	-	2.644	-	12.751
$\theta_{(top6\times size)-}$	-	7.529	-	5.064	-	12.393	-	8.623	-	6.401
Std.Err.	-	3.367	-	1.871	-	8.315	-	5.789	-	11.109
LR p-value	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000
$\lvert w_i \rvert \times 100$	0.068	0.068	0.272	0.272	0.154	0.154	0.210	0.210	0.291	0.291
$\max\ w_i \times 100$	1.550	2.545	2.493	3.597	3.650	4.655	2.853	2.744	3.955	4.457
$\sum I(w_i = 0)/N_t$	0.000	0.491	0.000	0.283	0.000	0.427	0.000	0.382	0.000	0.427
$\min\ N_t$	-	707	-	203	-	313	-	292	-	167
$\max\ N_t$	-	4518	-	921	-	1585	-	1204	-	778
$\bar{r}$	0.103	0.134	0.103	0.156	0.131	0.159	0.110	0.149	0.114	0.143
σ	0.133	0.139	0.076	0.084	0.130	0.132	0.072	0.081	0.079	0.088
$CE(r)$	0.058	0.086	0.088	0.139	0.094	0.121	0.097	0.133	0.100	0.127
$SR(r)$	0.472	0.674	0.828	1.376	0.700	0.903	0.969	1.338	0.933	1.175
α	-	0.007	-	0.011	-	0.007	-	0.009	-	0.007
β	-	1.038	-	1.082	-	1.011	-	1.039	-	1.022
$\sigma(\epsilon)$	-	0.020	-	0.021	-	0.012	-	0.031	-	0.034