Market Timing and Investment Selection: Evidence from Real Estate Investors*

Yael V. Hochberg
Kellogg School of Management
Northwestern University & NBER

Tobias Mühlhofer
Kelley School of Business
Indiana University

January 2011

Abstract

In this paper, we explore fund managers' abilities to generate abnormal profits in the real estate market, a market characterized by relative inefficiency compared to the publicly-traded equities market. We adapt the Daniel, Grinblatt, Titman and Wermers (1997) measures of 'Characteristic Timing' and 'Characteristic Selectivity' to measure public and private real estate investors' ability to successfully time their portfolio weightings and select properties that outperform average properties of similar type. Using data on publicly traded REITS as well as property transactions data for private entities, we find that the vast majority of both public and private portfolio managers exhibit little market timing ability. Public portfolio managers exhibit substantial variation in their ability to successfully select investments, while private portfolio managers have near zero selection ability across the board. Variation in managerial ability to time markets or select investment classes does not appear to be related to observable portfolio characteristics, suggesting possible heterogeneity in managerial skill.

*We thank Jim Clayton and Jeff Fisher for helpful discussions and suggestions. We thank NCREIF for provision of data on private property holdings. Both authors gratefully acknowledge funding from the Real Estate Research Institute. Hochberg additionally acknowledges funding from the Zell Center for Risk Research at the Kellogg School of Management. Address correspondence to y-hochberg@northwestern.edu (Hochberg), tmuhlhof@indiana.edu (Mühlhofer).

1 Introduction

Discussions regarding the generation of abnormal profits through active trading have long held a prominent position in the finance literature. Beginning with Jensen (1968), a large literature has explored the ability of mutual fund managers to systematically picks stocks and time their investments so as to generate abnormal performance and justify the fees and expenses of active money management. Despite the volume of articles in this vein, evidence on the systematic ability of portfolio managers to generate abnormal profits has yielded results that are mixed at best, and generally negative. These findings are often ascribed to the fact that the stock market is overall generally considered to be highly informationally efficient. In this study, we revisit the question of whether and how abnormal profits are achieved by informed institutional investors, utilizing an alternative asset class (real estate) that is traded in a less efficient market than that for common market-traded equities and for which abnormal profits by informed investors are therefore considered anecdotally to be more common.

While the discussion of abnormal profit generation in inefficient markets can apply to any number of asset classes that trade in private markets, most of these markets suffer from a lack of data availability. The real estate market is an exception in this respect, and therefore provides an excellent laboratory for constructing a systematic view of whether and how informed institutional-level investors can generate abnormal profits through active trading in a somewhat inefficient market. Indeed, existing studies of the real estate market suggest that property markets display evidence of predictability (see e.g. Liu and Mei (1992, 1994), Barkham and Geltner (1995), Case and Shiller (1990), Case and Quigley (1991)). Furthermore, studies employing simulated technical trading strategies suggest that market timing profits can be made in the real estate property market (Geltner and Mei (1995) and Mühlhofer (2009)).

Abnormal profits (or the lack thereof) for mutual funds in the stock market have been studied extensively in the literature (see e.g. Jensen (1968, 1969), Brown and Goetzmann (1995), Gruber (1996), Carhart (1997)). The common theme that emerges from these studies is that true risk-adjusted abnormal profits are rare in stock portfolios held by mutual funds, and when found, such profits lack persistence. A useful methodology for examining abnormal performance is proposed by Daniel, Grinblatt, Titman and Wermers (1997), who distinguish between *timing* (the ability to be invested in broad portfolios representing a certain style when these outperform and to be out of them when they do not) and *selectivity* (the ability to select individual stocks within a style which outperform a broad style portfolio on a regular basis). The Daniel et al. (1997) methodology and its distinction between market timing and investment selection provides a starting point characterizing trading strategies in the real estate market, in that it provides a method for characterizing exactly how informational advantages are exploited. In the mutual fund literature, results from such decomposition point to some limited degree of ability in terms of *selectivity*, but nearly no ability in terms of *timing* on the part of managers (Daniel et al. (1997) as well as for example Wermers (2003), Kacperczyk, Sialm and Zheng (2005)).

In this study, we make use of a complete dataset of property trades by institutional-grade REITs who are legally mandated to report such trades to the SEC in their 10-K and 10-Q reports, thus providing both complete trading information and eliminating selection bias. We augment this information with a dataset of property trades made by portfolio managers of private entities, such as commingled real-estate funds, who have legally committed to disclose this information to a private data collector under a strict non-disclosure agreement. We thus are able to identify and analyze individual real estate property holdings and returns for a large set of public and private portfolio managers.

There are are a number of advantages to directly evaluating the portfolio of property holdings of REIT and private investors, rather than at the mutual funds of REITs (see e.g. Kallberg, Liu and Trzcinka (2000), Hartzell, Mühlhofer and Titman (2010) for studies of REIT mutual fund performance). As we are able to observe the individual property characteristics, we can design benchmarks that are better able to capture the particular characteristics of portfolio manager holdings. Knowing the timing of individual property transactions allows us to more accurately compute portfolio weights across time. Additionally, as is the case in exploring individual holdings in mutual funds in Daniel et al. (1997), constructing returns from portfolio holdings allows us to avoid concerns related to comparison of net-of-fee fund returns to benchmarks that ignore transaction costs.

Using the property transaction data, we compute manager-specific characteristic timing and characteristic selectivity measures. We use property portfolio index returns at a CBSA level, a state level, a divisional level, a regional level and at the whole national level. The resulting characteristic timing and characteristic selectivity measures suggest that the vast majority of both public REIT and private portfolio managers possess little or even negative ability to successfully time their investments vis a vis the market regardless of the level of benchmark specialization. However, a small number of top quartile managers do appear to possess statistically significant ability to time the market at all levels of specialization. While there appears to be little dispersion and little ability on the part of private managers to successfully select investments versus a benchmark, public portfolio managers have substantial dispersion in their characteristic selectivity ability, and in the top half of the distribution, appear to positively enhance returns through investment selection.

When we regress timing and selectivity on manager and portfolio characteristics, we find little in the way of a systematic relationship between portfolio characteristics and selection ability.

Private managers whose portfolios are more specialized by property type or property subtype appear to have better characteristic selectivity across property types and subtypes. Our regression models, however, can only explain a small amount of the variation in selection ability, suggesting that individual manager skill is likely an important driver of selection success. In contrast, while overall timing ability appears to be negligible or negative for the population of both public and private portfolio managers, portfolio characteristics can explain a larger portion of the variance in timing ability. Characteristic timing appears to be positively related to portfolio average property holding period for public portfolio managers, while it is negatively related to portfolio average property holding period for private portfolio managers. In contrast to the characteristic selectivity measures, our models for relating portfolio characteristics to market timing are able to explain a more reasonable proportion of the variation in this ability.

The contribution of our paper to the existing literature is threefold. First, our work contributes to the large literature exploring the generation of abnormal returns by portfolio managers. In exploring beyond the abilities of mutual fund managers to generate trading profits in public markets, our work contributes to an emerging literature that attempts to generate a systematic view of how potential trading profits are made in alternative asset markets (see e.g. Cochrane (2005), Kaplan and Schoar (2005), Ljungqvist and Richardson (2003), Gompers, Kovner, Lerner and Scharfstein (2008) in private equity and venture capital markets and Bond and Mitchell (2010) in real estate). While existing studies of alternative asset markets are often limited by data availability[1], the real estate transaction data we employ in this study allows us to conduct a detailed analysis of individual holdings in such markets. While contemporaneous studies such as Bond and Mitchell (2010) also use

[1]Data limitations in VC and PE include such difficulties as being able to observe only venture-capital financed firms that went public, having to rely on voluntarily reported investment returns, or by being forced to use other indirect public-market related measures to infer information about the more inefficient private market.

private real estate fund data to assess outperformance, their work focuses on performance measures such as *alpha* at the fund level, whereas we assess measures of timing and investment selection ability that may drive outperformance. Second, our findings contribute to an emerging discussion in the real estate literature on the choice of portfolio specialization. To date, existing work has focused primarily on geographic diversification (see e.g. Hartzell, Sun and Titman (2010)). Our findings shed additional light on the importance of portfolio manager specialization in this industry. Finally, our work provides additional empirical support for the importance of financial intermediation in the gathering of specialized knowledge and efficiencies. REIT portfolio managers, who by definition specialize and concentrate solely on investment in the real estate market, appear to have much greater ability to select investments versus a benchmark of similar characteristics. Private portfolio managers, who primarily represent multi-asset, commingled funds, appear in contrast to have little selection ability, even at the upper tail.

The remainder of this paper is structured as follows. Section 2 describes the data we employ for our analysis. Section 3 details our adaptation of the Daniel et al. (1997) methodology. Section 4 details our empirical findings. Section 5 discusses and concludes.

2 Data

The data for our analysis are obtained from three primary data sources. Property transaction data for REIT portfolio managers are obtained from SNL Financial, which aggregates data from 10-K and 10-Q reports of a large sample of institutional-grade publicly traded REITs. The SNL Financial DataSource dataset provides comprehensive coverage of corporate, market, and financial data on publicly traded REITs and selected privately held REITs and REOCs (Real Estate Operating Companies). One part of the data contains accounting variables for each firm, and the other contains a listing of properties held in each firm's portfolio, which we use for this study. For each property, the dataset lists a variety of property characteristics, as well as which REIT bought and sold the property and the dates for these transactions. By aggregating across these properties on a firm-by-firm basis in any particular time period, we can compute a REIT's fractional exposure to particular sets of characteristics such as property type and geographic segment. The SNL REIT sample runs from Q2 1995 through Q4 2008.

Property transactions data for private real estate portfolio managers are obtained from the National Council of Real Estate Investment Fiduciaries (NCREIF), which collects transaction-level data for for private entities (primarily pension funds). For a private pension fund, having one's properties be part of NCREIF's portfolio is generally considered highly desirable, in that this gives the fund prestige. Because NCREIF's policy is to only report data on high-grade institutional-quality commercial real estate (which it uses for its flagship industry index, the NPI) being part of NCREIF's database confirms a level of quality on the part of the investor. It is not possible for an investor to report performance only in certain quarters and not in others, as some times happens with private equity; NCREIF membership constitutes a long-term commitment. Further, data reported by NCREIF members is treated by the organization under a strict non-disclosure agreement.[2] Thus, manipulating performance numbers would be ineffective because this could not help the investor signal quality. Because NCREIF members are both willing and able to fully and confidentially report this data to NCREIF, this arrangement gives us the opportunity to examine trades in a large private asset market, in a more complete and unbiased way than the data used in past studies on other alternative asset classes. This data source thus helps us overcome issues such as selection- and survivorship bias, which plague much of the private-equity, hedge-fund, and

[2] As academic researchers, we are given access to NCREIF's raw data under the same non-disclosure agreement.

venture-capital literature. The NCREIF sample runs from Q1 1978 through Q2 2010.

Real estate market returns, both aggregate and disaggregated, are obtained from the National Property Index (NPI) series, also compiled by NCREIF from this individual property data. The NCREIF NPI is considered the de-facto standard performance index for investible US commercial real estate. Index series are available on a national level, as well as disaggregated by region, division, state, CBSA, property type, property sub-type, and all possible interactions of these. In order to construct our measures of trading ability, we match properties with their respective indices at each level of aggregation. [3]

As our goal is to observe managers' abilities to generate profits through active management, we employ only properties that were both bought and sold within the sample period, and thus for which we have round trip transaction returns. In future versions of the paper, we will relax this condition where possible to account for properties purchased within the sample period and not yet sold, as well as properties purchased prior to the start of the sample and sold with the sample period.

Our data allow for many levels of disaggregation at both the geographical and property type levels, as well as their interactions. While this creates many degrees of freedom for analysis, it allows us a very complete view of how value may be generated by managers through characteristic timing or selectivity. NCREIF subdivides property types into subtype for all types, however SNL does not provide certain subtypes for some property types. Table 1 describes the breakdown of property types and sub-types as well as geographical regions and sub-regions for our REIT and private manager samples. Our data can additionally be disaggregated to the state and Core-Based

[3]The price appreciation portion of the NPI series is based on appraised values where transaction prices are not available. The biases associated with this data are widely documented. We plan to account for this limitation in a future version of this paper.

Statistical Area (CBSA) level (for brevity, we do not detail State and CBSA-level breakdowns in the table). There are five major property type categories in our datasets: Apartment, Hotel, Industrial, Office and Retail, with all but hotel broken down into two to eight further subtypes (e.g. Apartment: Garden, Apartment: High-rise and Apartment: Low-rise). Additionally, properties are classified as belonging to one of four Regions: East, Midwest, South and West, which in turn are broken down first into two Divisions each (e.g. East: Mideast and East: Northeast) and then further by State and CBSA (not detailed). For each property type and subtype as well as each Region and Division, the table details the number of unique properties transacted in by REIT and private portfolio managers portfolios.

Table 2 presents summary statistics for the two property datasets. The table presents time-series statistics of quarterly holdings. In the upper panel, we presents distributional statistics for the REIT properties, and in the lower panel, distributional statistics for the NCREIF private portfolio data. Our REIT portfolio sample contains 185 portfolio managers transacting in 9,516 properties. In a given quarter, the average (median) portfolio manager holds in a portfolio consisting of 20.64 (14.17) million square feet of property, with an individual average property size of 176,200 (109,400) square feet, spread across an average (median) of 10.4 (6) CBSAs. The average (median) manager in a given quarter holds 1.67 (1) types of properties in their portfolio, and 2.58 (2) sub-types. In a given quarter, our REIT portfolio managers have an average (median) geographic concentration (as measured by Hirschman-Herfindahl Index or HHI) ranging from 0.55 (CBSA) to 0.74 (Region) depending on level of geographic disaggregation, and an average property type concentration (HHI) of 0.83 by property subtype and 0.91 by property type. The average (median) manager is present in the sample for 7.45 (7.5) years of the 1995 to 2008 sample period.

In contrast, private portfolio managers hold slightly smaller portfolios by square feet, consisting of somewhat larger individual properties, and invest in a larger number of geographical regions and property types. Our NCREIF private portfolio sample contains 118 portfolio managers transacting in 6,787 properties. In a given quarter, the average (median) portfolio manager holds a portfolio consisting of 17.75 (12.72) million square feet of property, with an individual average property size of 246,000 (156,000) square feet, spread across an average (median) of 21 (13.5) Core-Based Statistical Areas (CBSAs). The average (median) private portfolio manager in a given quarter holds 3.1 (3) types of properties in their portfolio, and 6.1 (5) sub-types. In a given quarter, our REIT portfolio managers have an average geographic concentration (as measured by Hirschman-Herfindahl Index (HHI)) ranging from 0.43 (CBSA) to 0.62 (Region) depending on level of geographic disaggregation, and an average property type concentration (HHI) of 0.59 by property subtype and 0.69 by property type. The average (median) private portfolio manager is present in the sample for 10.95 (8.38) years of the 1978 to 2010 sample period.

3 Methodology

In order to assess and qualify managers' abilities to generate profits through active management, we adapt the methodology of Daniel, Grinblatt, Titman and Wermers (1997) (DGTW) for our purpose. DGTW develop a decomposition of mutual fund manager returns, which includes two primary components of interest to this study: managers' ability to time the market in selecting when they enter and exit individual holdings or classes of holdings, and managers' ability to select individual investments or subclasses of investments from within a pool of investments with similar characteristics.

To measure managers' ability to time market entry and exit, DGTW develop a *characteristic timing* measure for mutual funds, defined as follows:

$$CT_t = \sum_{j=1}^{N}(w_{j,t-1}R_t^{b_j,t-1} - w_{j,t-13}R_t^{b_j,t-13}) \quad (1)$$

In this expression $w_{j,\tau}$ is the fraction a fund invested into stock j at the end of time period τ and $R_\tau^{b_j,\tau-1}$ is the return to a passive portfolio that mirrors the characteristics of stock j. This measure will be positive for any time period in which a fund's weighted return derived from exposure to a particular security characteristic exceeds the weighted returns from that fund's exposure to this characteristic a year earlier. If the manager increases portfolio exposure to a characteristic in an upturn and decreases exposure in a downturn this demonstrates positive timing ability.

We adapt this measure for our study as follows. For every manager in the NCREIF dataset, we observe the properties held by him at the end of every quarter. For each property, we observe size as well as type, sub-type and the exact location. To compute weights that are analogous in function to those used by DGTW, we use the fraction of the manager's total square footage under management in a particular quarter which is constituted by a particular property (i.e. individual property square footage divided by total portfolio square footage). For characteristics, we use property sub-markets, whose returns are given by NCREIF's total return indices. For example, if a manager owned an office building in Chicago's CBD in the first quarter of 2006, the relevant return to the passive portfolio that mirrors this characteristic would be the total return to NCREIF's Chicago CBD Office sub-index for the quarter. Summing up weights across all properties managed by this manager in the particular quarter and sub-market yields the manager's total fractional exposure to the characteristic, which is combined with the relevant NCREIF sub-index to generate the weighted return for that quarter. Analogously, we construct fractional exposure and characteristic return a year earlier and measure the weighted return the same way. In this case, a high positive value would be generated by the manager's decision to increase portfolio exposure to Chicago CBD Office, ahead of a rise in this market and/or decrease exposure ahead of a slump. This would be considered positive timing ability with respect to this market overall. We proceed analogously for all other characteristics to which the manager's portfolio is exposed. The sum across all characteristics yields the manager's CT measure for that quarter. We repeat this procedure for each quarter the manager appears in our dataset, and then compute time-series statistics by manager.

In order to assess the level of specialization at which a manager potentially provides value, we construct our CT measures using various levels of aggregation in our characteristic benchmarks. We use property portfolio index returns at a CBSA level, a state level, a divisional level, a regional level and at the whole national level. At each of these levels we use as benchmarks the property sub-type, the property type, and the entire property market. Continuing the example above, for a manager's exposure to Chicago CBD Office in the first quarter of 2006, we construct a CT measure using the Chicago CBD Office index returns for 2006Q1 and 2005Q1 respectively, then construct a CT measure using the overall Chicago office index and one using the overall Chicago property index. Then we construct three CT measures using the manager's Illinois exposure (one for CBD office, one for overall office, and one for overall property). Then we construct three CT measures for the manager's West-North-Central division exposure, then three more using the manager's Midwest regional exposure, and three at the national level. We compute separate time-series statistics for each manager at each level of specialization and then summarize the cross-section of manager time-series statistics for each level.

To measure portfolio managers' ability to select investments within a class of similar characteristics, DGTW devise a *characteristic selectivity* measure, defined as follows:

$$CS_t = \sum_{j=1}^{N} w_{j,t-1}(R_{j,t} - R_t^{b_j,t-1}) \tag{2}$$

Here, $R_{j,t}$ is the return to property j itself, rather than a benchmark return, and all other notation is as defined above. A positive measure means that on average a fund manager selects specific stocks that outperform his or her benchmark portfolio. As with the CT measure, in DGTW's procedure this is computed every time period.

Due to the nature of property data, we make a more substantial modification to this measure. Given that we do not have a reliable quarterly price series for each property to compare with its benchmark, we conduct this measurement over the entire holding period return for each property, and then aggregate cross-sectionally to generate a single *manager characteristic selectivity* (MCS) measure for each manager at each level of specialization, as follows:

$$MCS_m = \sum_{j=1}^{N} \overline{w_j}(R_{j,t_0}^T - R_{b_j,t_0}^T) \tag{3}$$

In the above expression $\overline{w_j}$ constitutes manager m's average portfolio weight in property j during his entire holding period (t_0 to T) of this property. This is computed as the average square-footage of property j, divided by the total average square footage held by the manager in the entire dataset. Then, R_{j,t_0}^T is the total holding period return (both income and price appreciation) for property j and R_{b_j,t_0}^T is the total compounded return for the benchmark index with which property j is associated. Given that for REIT managers we do not have reliable purchase and sale prices for each property, we use the compounded total return for the local NPI (for the same CBSA and property type as the property itself) as R_{j,t_0}^T, to proxy for the actual holding-period return to the property.[4] To ensure consistency, we use the same proxy approach for private managers, at this stage of the project. A positive difference indicates that the manager has selected a property that performed better than the average property in that particular market would have. If the manager can do this over his entire portfolio, this manager has selective abilities.

Once again, we compute these measures for all degrees of specialization of the benchmark portfolio. Continuing the previous example, we would compare the total holding period return derived from a particular Chicago CBD Office building from 2000 through 2008, to the total return to the Chicago CBD Office market index during this same time period. In the next run we would compare the property return to the return to the overall Chicago Office market, and so forth, once again using all levels of aggregation or specialization, geographically and by type or subtype. In this case, since the CBSA/Type portfolio serves as a benchmark, we do not construct this measure at the CBSA/Type and CBSA/Subtype levels, but only using benchmarks of higher levels of aggregation.

Once we have constructed our performance measure, we then investigate which managers are more or less successful, as a function of various observable characteristics. We do this by running cross-sectional regressions as follows:

$$CT_i = \alpha + \beta_1 spec_i + \beta_2 size_i + \beta_3 log(size_i) + \beta_4 holding.per_i + \epsilon_i \tag{4}$$

$$CS_i = \alpha + \beta_1 spec_i + \beta_2 size_i + \beta_3 log(size_i) + \beta_4 holding.per_i + \epsilon_i \tag{5}$$

In the equations above, the dependent variables are, for each manager, the time-series average CT measure and the manager's MCS measure, respectively. The independent variables are $size_i$,

[4] Crane and Hartzell (2007) use an analogous proxy in their study and find that the returns derived through this proxy have a correlation of more than .96 with the actual returns, where available.

manager i's average portfolio size, for which we include both the level and the natural logarithm; $holding.per_i$, defined as the average number of years a manager holds a property in his portfolio; and $spec_i$, which measures the level of specialization of a manager's portfolio, and is computed as a Hirschman-Herfindahl Index, defined as follows:

$$H_{i,t} \quad = \quad \sum_{s=1}^{N} w_{s,t}^2 \tag{6}$$

where $w_{s,t}$ is manager i's fractional exposure to submarket s in time period t (computed as the sum of the fractional exposures to each property within a submarket). In Equation 4, $spec_i$ becomes the time-series average $H_{i,t}$ for manager i. In Equation 5 $spec_i$ is computed cross-sectionally, as

$$spec_i \quad = \quad \sum_{s=1}^{N} \overline{w_s}^2 \tag{7}$$

Both these measures will be one if a manager held all his properties in one single sub-market and will approach zero, the more a manager is diversified among sub-markets.

We estimate a version of Equations 4 and 5 for performance measures computed with respect to benchmarks at all the levels of aggregation we employ, and we adapt the specialization measures accordingly. We also estimate separate regressions for public and private portfolios. To start with, we estimate two CT and two CS regressions (one each for public and private), using the national type and subtype benchmarks. In these regressions, we use a specialization measure by type and subtype only. We then estimate two equations for each measure using the combined disaggregation by geographic division and type as well as subtype. In this case, we use a combined specialization measure by region and type or region and subtype.

4 Empirical Results

We begin our empirical analysis by computing the CT and CS measures described in Section 3 for both public REIT managers and private portfolio managers.

4.1 Characteristic Timing

Table 3 presents distributional statistics from the cross-section of portfolio managers in the public and private samples. To obtain the statistics in the table, we first compute, for every manager in every quarter, the CT_t measure described in Equation (1). For each manager we then compute a time-series average over the quarters for which the manager is active in the sample, to obtain a single average CT statistic per manager. The table displays the mean, standard deviation, minimum, first quartile, median, 3rd quartile and maximum of these measures across managers. We compute these measures relative to benchmarks at both the geographical and property type levels, as well as interactions between the two. For ease of interpretation, these distributional statistics are illustrated in Figure 1. The boxes represent the inter-quartile spread of the distribution, while the whiskers demarcate 1.5 times the interquartile range from the edge of box. The circles represent outliers that do not fall within the whiskers.

As is apparent both from the table and the figure, neither the public nor private portfolio managers appear to exhibit particular skill at timing versus the various levels of benchmarks. If anything, both private and public managers appear to exhibit negative timing ability with respect to characteristic portfolios at essentially all levels of specialization. From the bottom of the distribution up to and including the third quartile, we observe that the point estimates for managers' mean CT measures are negative. Only in the top quartile of the distribution are there managers with positive characteristic timing ability, with the top managers consistently able to positively time characteristics, measured at all levels of specialization.

As an illustrative example, consider characteristic timing as measured against the State/Type benchmark for private portfolio managers. The worst portfolio manager in the sample exhibits a characteristic timing measure of -2.2% per annum, with the 25th percentile of managers logging in a -0.55% per annum versus the benchmark. The median manager earns -0.4% per annum due to timing, and the 75th percentile manager exhibits a timing ability that accords him -0.1% per annum. The manager most successful at timing in our sample earned a mere 1.1% per annum from timing. Depending on the benchmark against which the ability to select individual CBSA/Type combinations is measured, the top portfolio managers (public or private) earn between 0.37% per annum (State/Type) to 1.7% per annum due to ability to time investment versus the benchmark.

To better understand whether some managers are able to successfully and significantly time the market versus the characteristic benchmarks, Table 4 presents distributional statistics for the t-statistic testing the hypothesis that a manager has zero timing ability against the two-sided alternative. As for the previous table, for each manager in each quarter, we compute CT_t as in Equation1, and then compute a time series average to obtain a single average CT score per manager. Following Hartzell, Mühlhofer and Titman (2010), we then compute a t-statistic for the hypothesis that this time-series mean CT is different than zero for each manager. The table presents the distributional statistics of these t-statistics. For ease of interpretation, these distributional statistics are illustrated in Figure 2. The boxes represent the inter-quartile spread of the distribution, while the whiskers demarcate 1.5 times the interquartile range from the edge of box. The circles represent outliers that do not fall within the whiskers.

Looking at the distributional statistics in the table and as illustrated by the figure, it is apparent that from the median up to and beyond the third quartile, the timing abilities of private managers are actually statistically indistinguishable from zero, while they appear to be significantly negative for public portfolio managers. Below the median, managers' timing abilities are significantly negative for both private and public portfolio managers, with the exception of a few more specialized benchmarks, by state and subtype, as well as by CBSA and subtype, where the entire inter-quartile range is indistinguishable from zero. However, it is also apparent that some managers in the upper quartile of both the private and public managers not only not only generate positive timing value on average, but indeed appear to possess significantly positive timing ability.

The results are surprisingly homogeneous throughout the different levels of benchmark specialization, suggesting that the distribution of timing abilities is very similar whether we assess managers' ability to time large national trends or particular submarkets and property types. There does seem to be, however, a very slight upward shift and a slightly larger dispersion in timing abilities as we employ more specialized benchmarks.

We must emphasize that these results must not necessarily be due to a managers' inherent abilities to read markets, but may be caused by the microstructure of the market in which they act. It is well known that the commercial property market suffers from slow execution of transactions and very high transaction costs, when compared to other asset markets. This aspect may be an important driver behind the timing results we observe, and we are not in a position to ascribe a definite underlying cause to the results we observe.

4.2 Characteristic Selection

Having examined managers' characteristic timing ability, we next proceed to examine characteristic selectivity. Table 5 presents the distributional statistics of the characteristic selectivity measure for the cross-section of public and private portfolio managers. To obtain the statistics for the table, we compute the MCS variable described in Equation (3) of Section 3. The MCS measure is computed for each manager by taking the difference between the return on the lowest available level of aggregation, CBSA/Type (CBSA interacted with property type) minus the benchmark return on various higher levels of aggregation, weighted by the portfolio manager's time-series average portfolio weight in that CBSA/Type category. This provides us with a single measure of characteristic selectivity per manager, for which we display distributional statistics across managers.[5] As CBSA/Type level allocations are used as the measure of actual investment selection relative to the category benchmark, the table naturally omits any statistics for the CBSA/Type- or CBSA/Subtype-level benchmarks.

For ease of interpretation, the distributions from the table are presented graphically in box plot form in Figure 3. Here as before, the boxes represent the inter-quartile spread of the distribution, while the whiskers demarcate 1.5 times the interquartile range from the edge of box. The circles represent outliers that do not fall within the whiskers. A number of patterns are readily apparent from both the table and the figure. There is little dispersion in the ability of private managers to select investments on characteristics, while there is substantial dispersion in the characteristic selectivity ability of public portfolio managers. Managers in the top quartile of public funds appear to have substantial characteristic selectivity ability, on the order of over 1.5% additional return per annum, regardless of level of benchmark. This suggests substantial variation in managerial ability to select investments within categories for public portfolio managers. In contrast, the means, median and interquartile range of characteristic selectivity ability for private managers are near zero.

As an illustrative example, consider selectivity as measured against the Divisional/Subtype benchmark for public REIT portfolio managers. The worst portfolio manager in the sample exhibits

[5]Because these measures are computed as a single cross-sectional weighted sum for each manager, we do not perform hypothesis tests for this measure as we lack a time-series of observations.

a selectivity measure of -11% per annum, with the 25th percentile of managers logging in a -1.5% per annum versus the benchmark. The median manager, however, earns roughly zero (-0.3% per annum) from selectivity, and the 75th percentile manager exhibits a positive selectivity ability of 0.6% per annum. The manager most successful at timing in our sample earned 9.6% per annum from selectivity. Depending on the benchmark against which the ability to select individual CBSA/Type combinations is measured, the top public REIT portfolio managers earn anywhere from 5.9% per annum (State/Type) to 18.1% per annum due to ability to select investment categories.

4.3 Timing, Selection and Portfolio Characteristics

A natural question arising from our findings on the CT and CS measure is which manager or portfolio characteristics predict timing or selectivity ability? Can we attribute timing and selection abilities to known characteristics, or are they attributable to individual manger skill? To get a handle on these questions, we undertake a regression analysis that relates our CT and CS measures to various manager and portfolio characteristics, such as specialization, square feet under management, and length of property holding periods.

Tables 6 and 7 present estimates from manager by manager cross-sectional regressions described by Eq.s 4 and 5. We estimate the regressions separately for public and private portfolios. We estimate these regression models for portfolio manager timing and selectivity performance measures computed with respect to benchmarks at all the levels of aggregation we employ, adapting the specialization measures accordingly with each level of aggregation. More specifically, we begin by estimating two CT and two CS regressions (one each for public and private), using the national type and subtype benchmarks. In these regressions, we use a specialization measure by type and subtype only. We then estimate two equations for each measure using the combined disaggregation by geographic division and type as well as subtype. In this case, we use a combined specialization measure by region and type or region and subtype. The independent variables, as described in Section 3 are the portfolio managers time-series average specialization (HHI), the level and log of the time series average of square footage under management for the portfolio manager, and the average average property holding period.

Tables 6 and 7 present estimates from our manager by manager cross-sectional regressions where the dependent variable is the manager's characteristic selectivity performance measure. In general, the models appear to have low explanatory power, suggesting a limited ability to systematically explain a significant portion of the variation in characteristic selectivity ability using observable portfolio characteristics. While public portfolio managers appear to vary widely in their selectivity ability, our regression estimate suggest that observable characteristics such as portfolio size, specialization and churn are not significantly correlated with manager's selection ability, suggesting a possible role for managerial skill in selecting investments versus a characteristic matched benchmark. Similarly, there is little in the way of significant correlation between portfolio characteristics and private portfolio manager selectivity measures. However, private managers that are more specialized by property type and subtype appear to be better at selecting investments within property type and subtype. At more disaggregated levels such as the interaction of property type and geography our models are unable to detect systematic patterns in selectivity by managers, although there is some weak evidence that here too managers with slower turnover tend to select better.

Tables 8 and 9 present estimates from our manager by manager cross-sectional regressions where the dependent variable is the manager's characteristic timing performance measure. In contrast to characteristic selectivity, where there appears to be some variation in ability to select investments versus a benchmark, managerial ability to time the market is less apparent in the summary data.

Our regression models, however, are better able to capture systematic patterns in the variability of timing ability than was the case for selectivity ability. The adjusted-R^2s for the models are much higher than for the characteristic selectivity models in the previous tables, ranging from 4.2% to 14.9% for the public manager regressions and from 1% to 8.7% for the private manager regressions. The estimates in Table 8 suggest a consistent positive relationship between slower portfolio turnover in public portfolio manager portfolios and timing ability, across all levels of disaggregation, and weaker evidence suggesting a negative correlation between portfolio size and timing ability. In contrast, we find the opposite pattern for private portfolio managers; here, managers with quicker property turnover appear to be those with high market timing ability. The estimates also suggest that more specialized managers are associated with better characteristic timing ability.

The lack of a systematic relation between observable portfolio characteristics such as size and specialization and timing or selection ability suggests that individual managerial skill is likely an important component of the variation in these abilities. While the data available to us limits our ability to explore this hypothesis in more detail, a natural question which arises for future research is how individual manager characteristics, such as experience, background, education, and so forth, might relate to the managers' ability to either time their property purchases and sales or to select individual properties or subclasses of investment versus characteristic matched similar investments.

5 Conclusion

Whether portfolio managers are able to earn abnormal returns through market timing or investment selection is an ongoing debate in the finance literature. In this paper, we explore portfolio manager investment abilities in an alternative asset market characterized by informational asymmetries that may be capitalized on by investors: real estate. We adapt the Daniel et al. (1997) characteristic timing and characteristic selectivity measures to individual property transaction data to compute measures of public REIT and private portfolio managers' abilities to successfully time the market and select investments.

Both public and private portfolio managers exhibit little ability to successfully time the market, on average, though the top quartile of portfolio managers appear to have significant timing ability. There is substantial variation in the ability of public portfolio managers to select investments, but little variation in the selection ability of private portfolio managers. We find little evidence of a systematic relationship between characteristic timing and selectivity abilities and observable portfolio characteristics, suggesting that individual manager skill is likely an important component of market timing and selection ability.

To the best of our knowledge, our study is the first to rigorously examine issues of market timing and investment selection of individual property transactions in the real estate market. As such, it can provide important insights for investors, portfolio managers and academics into how and which managers are able to earn abnormal profits in these markets.

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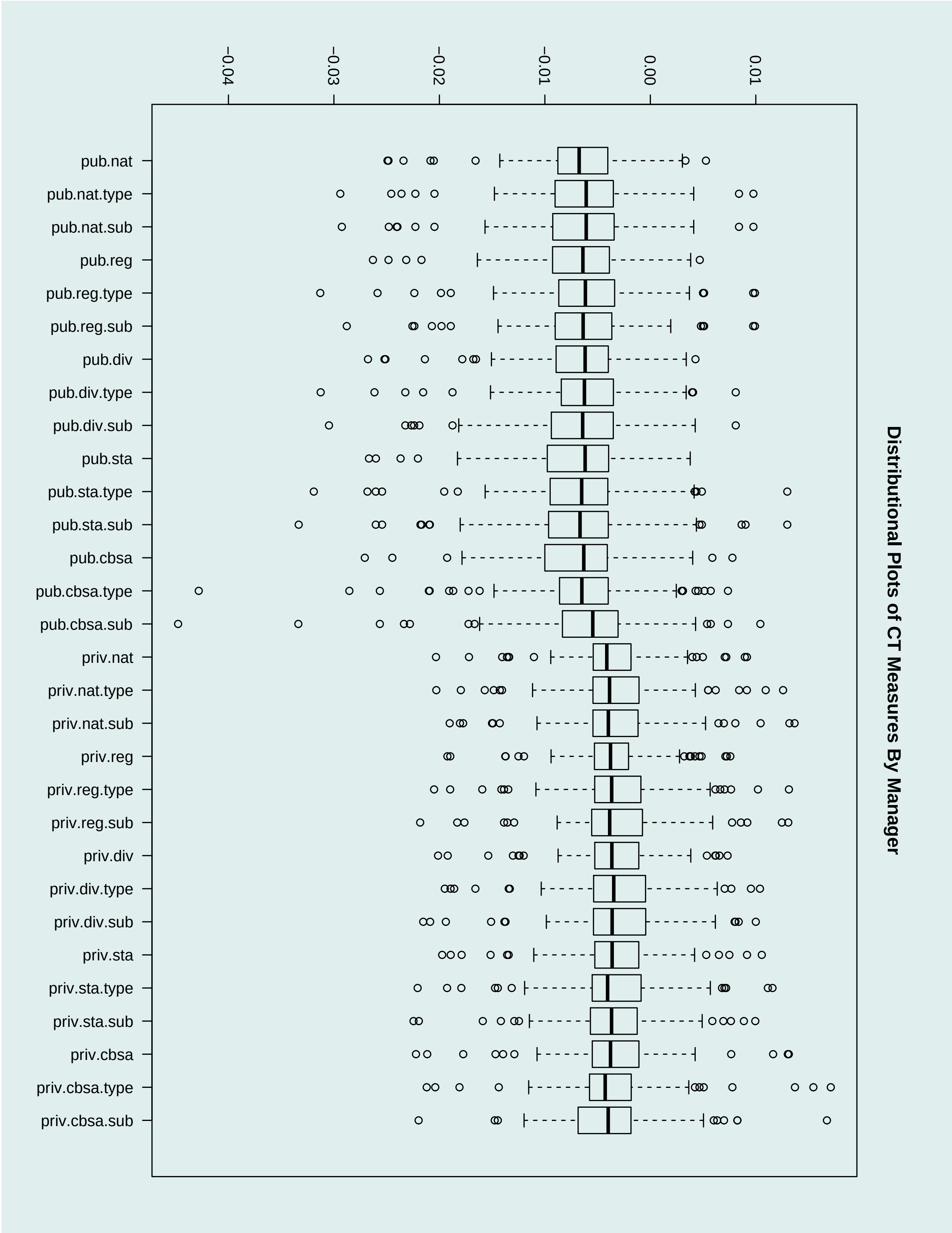

Figure 1: This figure shows box-and-whisker diagrams comparing the cross-sectional distributions of CT measures obtained by managers with respect to the various aggregation levels of benchmarks. The data presented includes REIT managers (starting with *pub*) and private managers (starting with *priv*)
.

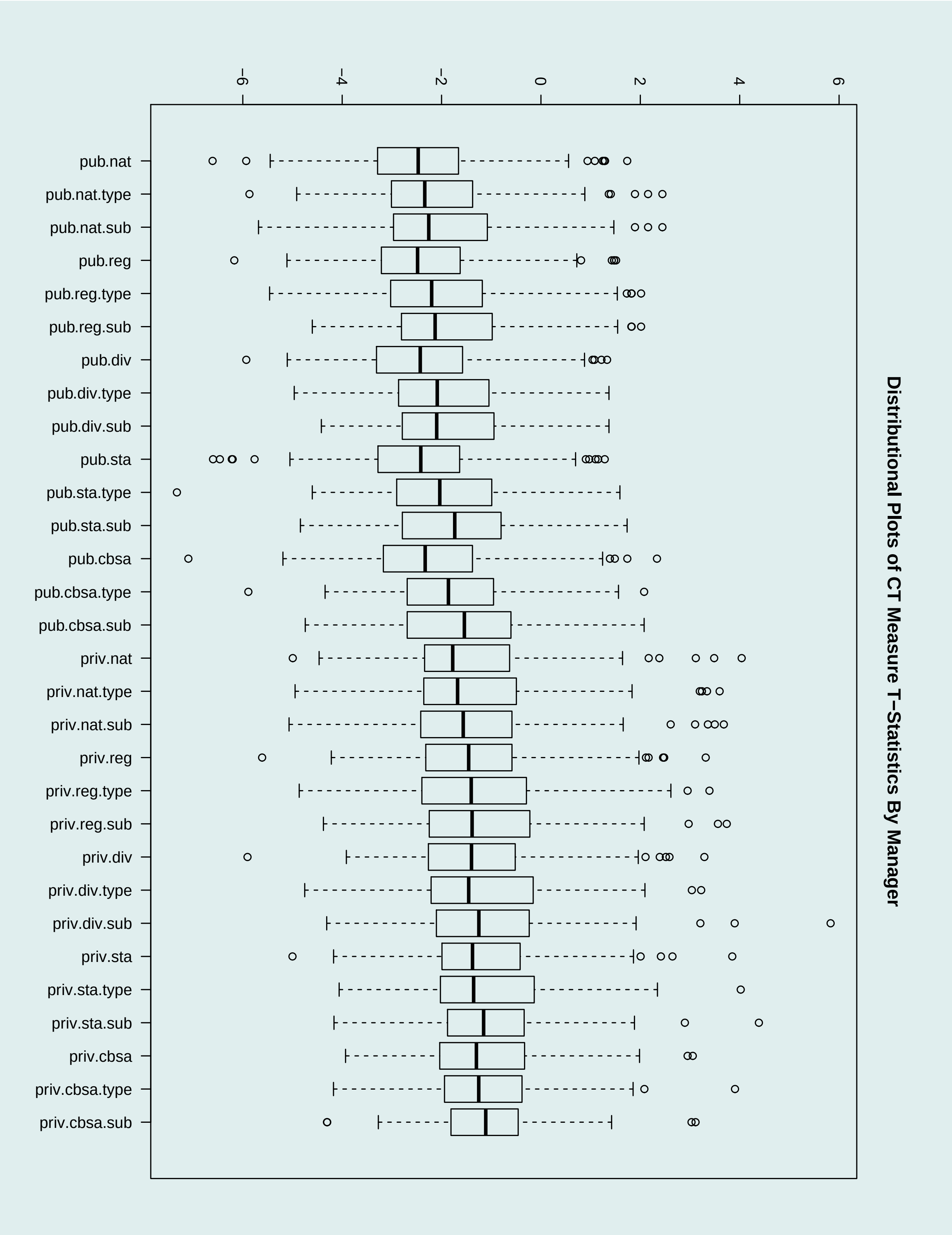

Figure 2: This figure shows box-and-whisker diagrams comparing the cross-sectional distributions of the t-statistic that a manager's CT-measure is different from zero. The data presented includes REIT managers (starting with *pub*) and private managers (starting with *priv*)
.

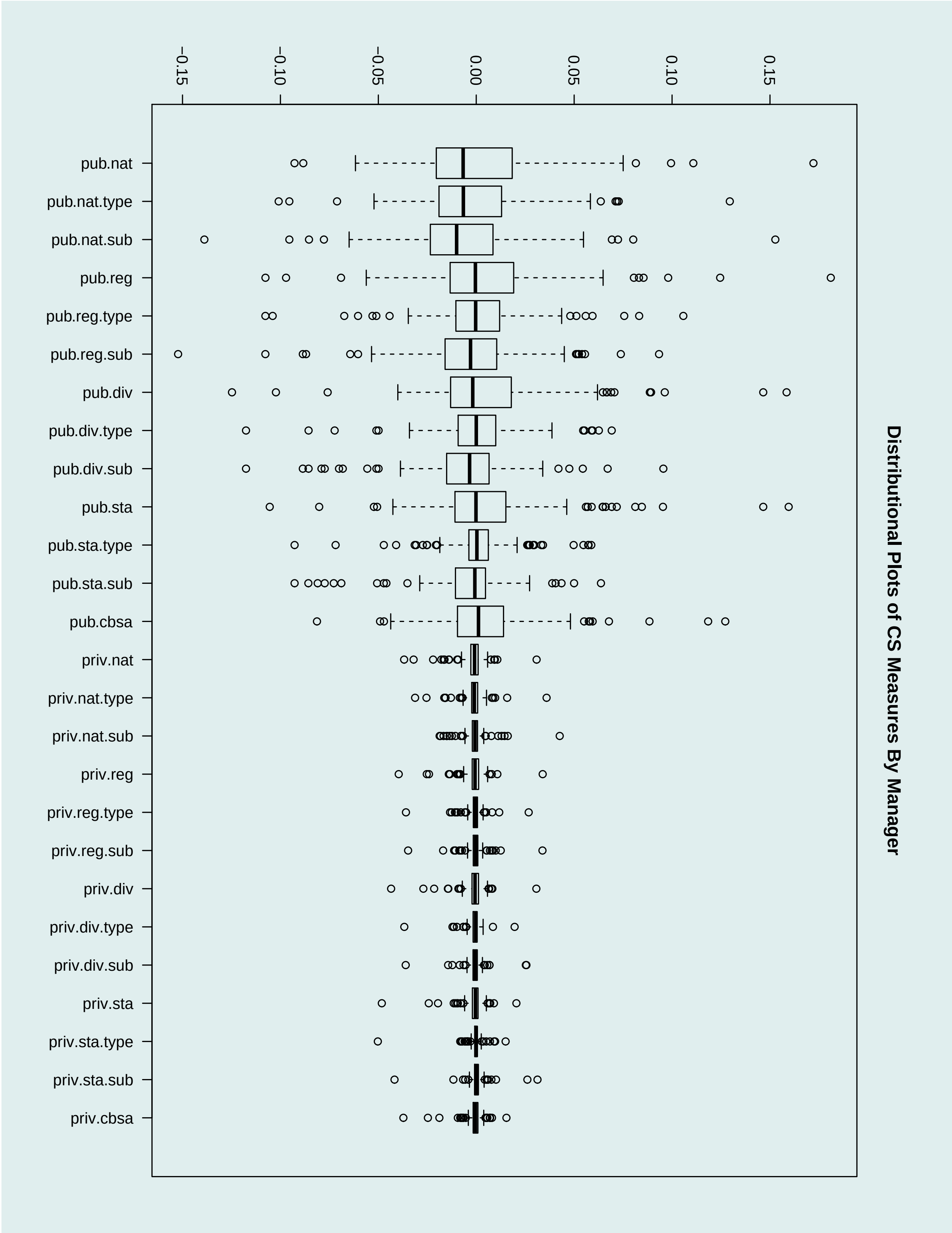

Figure 3: This figure shows box-and-whisker diagrams comparing the cross-sectional distributions of CS measures obtained by managers with respect to the various aggregation levels of benchmarks. The data presented includes REIT managers (starting with *pub*) and private managers (starting with *priv*)
.

Table 1: Subdivisions by Geography and Property Type

This table presents the numbers of properties held by private investors and REITs, organized by NCREIF Type, Subtype, Region, and Division. NCREIF also offers organizations by state and CBSA, which we do not present here.

		Private	**REITs**
Type and Subtype			
Apartment		1296	1368
	Garden	955	
	High-rise	121	
	Low-rise	65	
Hotel		96	21
Industrial		2330	1117
	Warehouse	1691	911
	R&D	373	112
	Flex Space	254	459
	Manufacturing	4	121
	Showroom	3	
	Other	26	76
Office		1942	3257
	CBD	410	3042
	Suburban	1495	215
Retail		1131	1676
	Community	375	
	Fashion/Specialty	13	
	Neighborhood	401	
	Outlet	3	41
	Power Center	36	22
	Regional	114	79
	Super Regional	65	
	Single Tenant	124	256
Regions and Divisions			
East		1427	2611
	Mideast	771	1183
	Northeast	656	1428
Midwest		1181	1739
	East North Central	826	1303
	West North Central	355	436
South		2012	2696
	Southeast	1079	1596
	Southwest	933	1100
West		2167	2470
	Mountain	571	622
	Pacific	1596	1848

Table 2: Summary Statistics

This table presents summary statistics for the sets of properties held by both private investors and Real Estate Investment Trusts.

	Mean	**Std. Dev.**	**1st Quartile**	**Median**	**3rd Quartile**
REITs					
Property Sizes (1000 Sq. ft.)	176.20	233.59	51.73	109.40	216.90
Portfolio Sizes (1000 Sq. ft.)	20,640	24,110	5,918.00	14,170.00	24,890
Portfolio Presence in Number of CBSAs	10.42	11.87	2.00	6.00	14.00
Number of Property Types in Portfolios	1.67	0.95	1.00	1.00	2.00
Number of Property Subtypes in Portfolios	2.58	1.98	1.00	2.00	3.00
Property Holding Periods (years)	3.89	1.85	2.58	3.58	5.02
Manager Number of Years in Sample	7.45	4.16	3.75	7.50	11.50
Manager HHI, by Region	0.74	0.25	0.53	0.76	1.00
Manager HHI, by Division	0.67	0.28	0.42	0.63	1.00
Manager HHI, by State	0.61	0.31	0.36	0.53	1.00
Manager HHI, by CBSA	0.55	0.32	0.26	0.45	0.88
Manager HHI, by Type	0.91	0.16	0.90	1.00	1.00
Manager HHI, by Subtype	0.83	0.21	0.67	0.95	1.00
Number of Sold Properties: 9,516		Number of Managers: 185			
Private Portfolios					
Property Sizes (1000 Sq. ft.)	246	305	85	156	294
Portfolio Sizes (1000 Sq. ft.)	17,750	19,637	5,308	12,720	22,580
Portfolio Presence in Number of CBSAs	21.00	22.84	4.00	13.50	29.75
Number of Property Types in Portfolios	3.076	1.32	2	3	4
Number of Property Subtypes in Portfolios	6.051	4.15	2.25	5	9
Property Holding Periods (years)	22.80	6.71	18.24	24.96	28.200
Manager Number of Years in Sample	10.95	8.51	4.06	8.38	16.440
Manager HHI, by Region	0.62	0.23	0.42	0.55	0.78
Manager HHI, by Division	0.54	0.26	0.33	0.46	0.74
Manager HHI, by State	0.48	0.27	0.27	0.42	0.67
Manager HHI, by CBSA	0.43	0.28	0.22	0.36	0.62
Manager HHI, by Type	0.69	0.21	0.51	0.66	0.88
Manager HHI, by Subtype	0.59	0.23	0.39	0.55	0.74
Number of Sold Properties: 6,787		Number of Managers: 118			

Table 3: Characteristic-Timing Measures: Means.

This table presents distributional characteristics across managers, for time-series means of quarterly Characteristic-Timing (CT) measures. The measures are computed relative to benchmarks at the National, Regional, Divisional, State, and CBSA level. At each geographic level of disaggregation, we use the benchmark for all property types combined, as well as benchmarks separated and matched by type and subtype. We include only managers for whom we can compute a CT measure over 12 quarters or more.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
Mean	−0.006652	−0.006303	−0.006490	−0.003578	−0.003379	−0.003339
StdDev	0.005083	0.005581	0.005784	0.004958	0.005423	0.005721
Min.	−0.024922	−0.029394	−0.029246	−0.020323	−0.020291	−0.019024
1st Qu.	−0.008765	−0.009031	−0.009250	−0.005416	−0.005438	−0.00544
Median	−0.006749	−0.006080	−0.006078	−0.004125	−0.003865	−0.00398
3rd Qu.	−0.004033	−0.003508	−0.003432	−0.001832	−0.001072	−0.001164
Max.	0.005271	0.009772	0.009772	0.009159	0.012585	0.013676
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
Mean	−0.006511	−0.006144	−0.006325	−0.003504	−0.0032021	−0.003217
StdDev	0.005118	0.005685	0.005696	0.004844	0.005574	0.005754
Min.	−0.026300	−0.031294	−0.028781	−0.019241	−0.0205016	−0.021823
1st Qu.	−0.009269	−0.008679	−0.009020	−0.005299	−0.0052732	−0.005559
Median	−0.006392	−0.006158	−0.006372	−0.003776	−0.0036636	−0.003853
3rd Qu.	−0.003881	−0.003385	−0.003650	−0.002067	−0.0008937	−0.000747
Max.	0.004688	0.009919	0.009919	0.007586	0.0131386	0.01308
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
Mean	−0.006545	−0.006231	−0.006602	−0.003417	−0.0031336	−0.003277
StdDev	0.005295	0.005760	0.005957	0.004952	0.005505	0.005596
Min.	−0.026769	−0.031255	−0.030468	−0.020127	−0.0194888	−0.0215318
1st Qu.	−0.008935	−0.008443	−0.009370	−0.005266	−0.0053767	−0.0053448
Median	−0.006181	−0.006250	−0.006415	−0.003648	−0.0034681	−0.0036214
3rd Qu.	−0.003982	−0.003502	−0.003530	−0.001093	−0.0004536	−0.0004663
Max.	0.004279	0.008097	0.008097u	0.007323	0.0103952	0.0099991
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
Mean	−0.006713	−0.006521	−0.006709	−0.003407	−0.0034281	−0.003543
StdDev	0.005399	0.006178	0.006844	0.005194	0.005472	0.005427
Min.	−0.026674	−0.031907	−0.033338	−0.019736	−0.0220617	−0.022454
1st Qu.	−0.009771	−0.009500	−0.009611	−0.005263	−0.0055108	−0.005682
Median	−0.006182	−0.006509	−0.006665	−0.003623	−0.0040536	−0.003676
3rd Qu.	−0.003954	−0.004030	−0.003998	−0.001094	−0.0008756	−0.001246
Max.	0.003781	0.012984	0.012984	0.010567	0.0115822	0.00995
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
Mean	−0.006704	−0.006878	−0.006196	−0.003551	−0.003641	−0.003871
StdDev	0.005303	0.006592	0.007551	0.005605	0.005912	0.005688
Min.	−0.027071	−0.042813	−0.044772	−0.02222	−0.021201	−0.021969
1st Qu.	−0.009976	−0.008608	−0.008231	−0.005495	−0.005767	−0.006848
Median	−0.006309	−0.006491	−0.005457	−0.003775	−0.004281	−0.003996
3rd Qu.	−0.004083	−0.003993	−0.003109	−0.001088	−0.001811	−0.001835
Max.	0.007783	0.007359	0.010431	0.013128	0.017109	0.016744

Table 4: Characteristic-Timing Measures: t-statistics.

This table presents distributional characteristics across managers, for t-statistics testing the hypothesis $H_o : CT = 0$ against the two-sided alternative, over a manager's time series of quarterly CT measure observations. The CT measures are computed relative to benchmarks at the National, Regional, Divisional, State, and CBSA level. At each geographic level of disaggregation, we use the benchmark for all property types combined, as well as benchmarks separated and matched by type and subtype. We include only managers for whom we can compute a CT measure over 12 quarters or more.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
Mean	−2.328	−2.055	−2.011	−1.359	−1.3015	−1.2853
Min.	−6.608	−5.866	−5.684	−4.9944	−4.9478	−5.0692
1st Qu.	−3.288	−3.009	−2.967	−2.3414	−2.3575	−2.419
Median	−2.470	−2.338	−2.258	−1.7752	−1.6775	−1.5637
3rd Qu.	−1.659	−1.375	−1.079	−0.6305	−0.4944	−0.5835
Max.	1.737	2.445	2.445	4.0398	3.5962	3.6803
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
Mean	−2.282	−1.977	−1.8535	−1.2976	−1.2451	−1.2067
Min.	−6.171	−5.461	−4.6013	−5.611	−4.8644	−4.3776
1st Qu.	−3.211	−3.024	−2.8070	−2.3175	−2.3959	−2.2475
Median	−2.482	−2.199	−2.1297	−1.4542	−1.403	−1.3855
3rd Qu.	−1.625	−1.180	−0.9803	−0.5827	−0.2921	−0.2229
Max.	1.512	2.015	2.0154	3.3164	3.3916	3.7398
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
Mean	−2.280	−1.879	−1.8251	−1.2175	−1.1707	−1.085
Min.	−5.930	−4.965	−4.4190	−5.9053	−4.7537	−4.311
1st Qu.	−3.309	−2.865	−2.7844	−2.2647	−2.2104	−2.1003
Median	−2.429	−2.087	−2.0975	−1.3972	−1.454	−1.2494
3rd Qu.	−1.577	−1.046	−0.9585	−0.5174	−0.1558	−0.2855
Max.	1.331	1.369	1.3692	3.2891	3.2251	5.8297
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
Mean	−2.337	−1.8824	−1.6887	−1.1591	−1.1621	−1.0654
Min.	−6.599	−7.3261	−4.8406	−4.9999	−4.0609	−4.1647
1st Qu.	−3.280	−2.9028	−2.7882	−1.9915	−2.0232	−1.8797
Median	−2.418	−2.0357	−1.7341	−1.3772	−1.3543	−1.1533
3rd Qu.	−1.636	−0.9896	−0.8065	−0.4187	−0.1351	−0.3379
Max.	1.284	1.5896	1.7341	3.8508	4.0208	4.3864
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
Mean	−2.184	−1.7862	−1.5699	−1.1531	−1.1062	−1.047
Min.	−7.095	−5.8880	−4.7428	−3.9321	−4.1751	−4.306
1st Qu.	−3.171	−2.6914	−2.6833	−2.0343	−1.9407	−1.81
Median	−2.330	−1.8618	−1.5411	−1.2989	−1.2517	−1.111
3rd Qu.	−1.385	−0.9538	−0.6108	−0.3327	−0.3807	−0.458
Max.	2.335	2.0769	2.0769	3.0556	3.9056	3.112

Table 5: Characteristic-Selectivity Measures

This table presents distributional characteristics for Characteristic Selectivity (CS) measures, computed for each manager over the cross section of that manager's portfolio. The CS measures are computed relative to benchmarks at the National, Regional, Divisional, State, and CBSA level. At each geographic level of disaggregation, we use the benchmark for all property types combined, as well as benchmarks separated and matched by type and subtype.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
Mean	0.0007442	−0.002251	−0.007690	−0.0017796	−0.0014051	−0.0007784
StdDev	0.034986	0.029172	0.032574	0.007318	0.006812	0.006637
Min.	−0.0927919	−0.100893	−0.138838	−0.0368219	−0.0312253	−0.0186941
1st Qu.	−0.0203993	−0.019018	−0.023435	−0.0027582	−0.0023054	−0.0019971
Median	−0.0066884	−0.006577	−0.010013	−0.0008682	−0.0009750	−0.0006384
3rd Qu.	0.0183747	0.012943	0.008558	0.0009639	0.0007192	0.0006529
Max.	0.1721918	0.129484	0.152741	0.0308248	0.0359202	0.0426279
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
Mean	0.0047360	0.0007451	−0.003776	−0.0011933	−0.0008977	−0.0005338
StdDev	0.034286	0.026762	0.029978	0.006846	0.005355	0.005871
Min.	−0.1076320	−0.1076789	−0.152247	−0.0395932	−0.0358835	−0.0347866
1st Qu.	−0.0133318	−0.0103935	−0.015849	−0.0020546	−0.0014861	−0.0015159
Median	−0.0004331	−0.0002934	−0.002910	−0.0006151	−0.0004743	−0.0003643
3rd Qu.	0.0191285	0.0119389	0.010336	0.0012221	0.0006419	0.0008116
Max.	0.1810584	0.1057498	0.093353	0.0339360	0.0267788	0.0338176
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
Mean	0.004457	$1.382e-04$	−0.005470	−0.0012375	−0.0009799	−0.0005275
StdDev	0.034219	0.023369	0.026209	0.006775	0.004716	0.005554
Min.	−0.124723	$-1.176e-01$	−0.117566	−0.0434662	−0.0367361	−0.0360228
1st Qu.	−0.013091	$-9.237e-03$	−0.015115	−0.0021553	−0.0016048	−0.0016437
Median	−0.001789	$1.687e-05$	−0.003385	−0.0006155	−0.0003390	−0.0005142
3rd Qu.	0.017902	$9.963e-03$	0.006552	0.0011580	0.0004810	0.0005239
Max.	0.158479	$6.918e-02$	0.095547	0.0306975	0.0195948	0.0256175
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
Mean	0.0051648	0.0012686	−0.004301	−0.0010991	$-4.535e-04$	$2.061e-04$
StdDev	0.032248	0.017948	0.022034	0.006493	0.005478	0.006087
Min.	−0.1054575	−0.0927606	−0.092761	−0.0482177	$-5.025e-02$	$-4.173e-02$
1st Qu.	−0.0108674	−0.0037492	−0.010573	−0.0019676	$-7.870e-04$	$-8.394e-04$
Median	−0.0001369	0.0003317	−0.000713	−0.0003978	$-3.478e-06$	$3.184e-05$
3rd Qu.	0.0151289	0.0061756	0.004675	0.0009184	$5.627e-04$	$1.078e-03$
Max.	0.1595487	0.0587504	0.063690	0.0205055	$1.500e-02$	$3.128e-02$
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
Mean	0.004292			−0.0009195		
StdDev	0.027002			0.005538		
Min.	−0.081327			−0.0372028		
1st Qu.	−0.009578			−0.0015680		
Median	0.001153			−0.0004120		
3rd Qu.	0.013937			0.0008575		
Max.	0.127173			0.0154197		

Table 6: Regression Results, CS Measures, Public Portfolios

Dependent variable: CS measure by manager, for various aggregation levels of benchmark. This table presents results from cross-sectional regressions, by manager, for public portfolios. The independent variables are portfolio specialization, portfolio size, log of portfolio size and average property holding period.

			National/Type		National/Subtype	
			Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)			0.023580	0.75	0.021944	0.63
spec.			0.002426	0.17	−0.012851	−1.00
size			0.000000	−0.23	0.000000	−0.30
log(size)			−0.002179	−1.17	−0.001593	−0.74
holding.per			0.000995	0.79	0.001145	0.81
$\overline{R^2}$			−0.002		−0.007	
F			0.921		0.703	
	Regional		Regional/Type		Regional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.028825	0.79	0.021113	0.74	0.016587	0.50
spec.	0.004872	0.38	−0.003180	−0.32	−0.008747	−0.76
size	0.000000	0.05	0.000000	−0.15	0.000000	−0.10
log(size)	−0.001983	−0.87	−0.001460	−0.82	−0.001704	−0.80
holding.per	0.000250	0.17	0.000830	0.72	0.002824	2.02*
$\overline{R^2}$	−0.012		−0.014		0.005	
F	0.524		0.429		1.183	
	Divisional		Divisional/Type		Divisional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.039263	1.08	0.018615	0.75	0.009429	0.32
spec.	−0.001639	−0.13	−0.006116	−0.70	−0.012077	−1.20
size	0.000000	0.03	0.000000	−0.17	0.000000	−0.07
log(size)	−0.002431	−1.07	−0.001183	−0.76	−0.000883	−0.47
holding.per	0.000362	0.25	0.000826	0.82	0.001763	1.38
$\overline{R^2}$	−0.012		−0.014		−0.004	
F	0.51		0.451		0.849	
	State		State/Type		State/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.030780	0.90	−0.002574	−0.13	−0.017343	−0.69
spec.	−0.001030	−0.09	0.001201	0.18	−0.006077	−0.7
size	0.000000	−0.06	0.000000	−0.36	0.000000	−0.64
log(size)	−0.001684	−0.78	0.000016	0.01	0.000369	0.23
holding.per	−0.000114	−0.08	0.000805	1.04	0.003371	3.15**
$\overline{R^2}$	−0.017		−0.017		−0.019	
F	0.331		0.308		0.253	
	CBSA		CBSA/Type		CBSA/Subtype	
	Coefficient	t-statistic				
(Intercept)	0.023766	0.83				
spec.	−0.005365	−0.53				
size	0.000000	−0.11				
log(size)	−0.000873	−0.49				
holding.per	−0.000735	−0.63				
$\overline{R^2}$	−0.019					
F	0.253					

Table 7: Regression Results, CS Measures, Private Portfolios

Dependent variable: CS measure by manager, for various aggregation levels of benchmark. This table presents results from cross-sectional regressions, by manager, for private portfolios. The independent variables are portfolio specialization, portfolio size, log of portfolio size and average property holding period.

			National/Type		National/Subtype	
			Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)			−0.011116	−1.08	−0.006990	−0.62
spec.			0.010728	2.78^{**}	0.009513	2.34^{*}
size			0.000000	0.33	0.000000	0.17
log(size)			0.000052	0.08	0.000148	0.20
holding.per			0.000063	0.65	−0.000068	−0.70
$\overline{R^2}$			0.072		0.048	
F			3.211		0.703	
	Regional		Regional/Type		Regional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.000949	−0.08	−0.004982	−0.50	−0.006005	−0.54
spec.	0.001239	0.29	0.000436	0.13	0.002419	0.65
size	0.000000	0.31	0.000000	−0.45	0.000000	−0.34
log(size)	−0.000350	−0.44	0.000091	0.14	0.000263	0.35
holding.per	0.000169	1.68°	0.000121	1.48	0.000032	0.36
$\overline{R^2}$	0		−0.01		−0.027	
F	0.989		0.727		0.262	
	Divisional		Divisional/Type		Divisional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.007230	−0.58	−0.006582	−0.76	−0.014162	−1.34
spec.	0.003034	0.71	0.000484	0.17	0.005178	1.47
size	0.000000	0.10	0.000000	−0.62	0.000000	−0.68
log(size)	0.000056	0.07	0.000188	0.33	0.000778	1.11
holding.per	0.000144	1.44	0.000128	1.78°	0.000016	0.19
$\overline{R^2}$	−0.004		0.003		−0.008	
F	0.901		1.074		0.765	
	State		State/Type		State/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.006363	−0.54	0.000384	0.04	−0.011783	−0.80
spec.	0.001564	0.39	−0.004018	−1.19	0.003654	0.80
size	0.000000	0.06	0.000000	−0.78	0.000000	−0.82
log(size)	0.000003	0.00	−0.000083	−0.13	0.000794	0.81
holding.per	0.000186	1.95°	0.000121	1.45	−0.000030	−0.31
$\overline{R^2}$	0.007		−0.002		−0.027	
F	1.198		0.95		0.273	
	CBSA		CBSA/Type		CBSA/Subtype	
	Coefficient	t-statistic				
(Intercept)	−0.006752	−0.68				
spec.	0.003194	0.93				
size	0.000000	0.31				
log(size)	−0.000007	−0.01				
holding.per	0.000168	2.09^{*}				
$\overline{R^2}$	0.028					
F	1.828					

Table 8: Regression Results, CT Measures, Public Portfolios

Dependent variable: Average CT measure by manager, for various aggregation levels of benchmark. This table presents results from cross-sectional regressions, by manager, for public portfolios. The independent variables are portfolio specialization, portfolio size, log of portfolio size and average property holding period.

			National/Type		National/Subtype	
			Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)			−0.003995	−0.61	−0.005778	−0.88
spec.			0.002801	1.05	0.003005	1.39
size			0.000000	0.79	0.000000	0.70
log(size)			−0.000613	−1.64	−0.000540	−1.38
holding.per			0.000793	3.07^{**}	0.000926	3.50^{***}
$\overline{R^2}$			0.089		0.113	
F			4.094		4.988	
	Regional		Regional/Type		Regional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.003725	−0.67	0.001172	0.19	−0.001396	−0.22
spec.	0.000735	0.41	−0.001102	−0.54	0.000109	0.05
size	0.000000	1.47	0.000000	0.94	0.000000	0.88
log(size)	−0.000563	-1.66°	−0.000719	-1.87°	−0.000609	−1.55
holding.per	0.000942	4.07^{***}	0.000719	2.74^{**}	0.000711	2.69^{**}
$\overline{R^2}$	0.137		0.07		0.056	
F	6.033		3.401		2.826	
	Divisional		Divisional/Type		Divisional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.003798	−0.65	0.002145	0.32	0.001407	0.19
spec.	0.000017	0.01	−0.001760	−0.82	−0.000835	−0.36
size	0.000000	1.26	0.000000	0.87	0.000000	0.87
log(size)	−0.000562	−1.58	−0.000771	-1.90°	−0.000809	-1.75°
holding.per	0.001067	4.40^{***}	0.000781	2.83^{**}	0.000858	2.75^{**}
$\overline{R^2}$	0.149		0.076		0.055	
F	6.551		3.613		2.757	
	State		State/Type		State/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.003888	−0.66	0.002818	0.40	−0.001027	−0.12
spec.	−0.000752	−0.40	−0.002537	−1.13	−0.001100	−0.40
size	0.000000	1.04	0.000000	0.68	0.000000	0.42
log(size)	−0.000529	−1.47	−0.000803	-1.89°	−0.000654	−1.20
holding.per	0.001088	4.44^{***}	0.000855	2.95^{**}	0.000990	2.71^{**}
$\overline{R^2}$	0.147		0.083		0.042	
F	6.463		3.876		2.242	
	CBSA		CBSA/Type		CBSA/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.006003	−0.97	−0.004250	−0.53	−0.006328	−0.57
spec.	0.000323	0.16	−0.001843	−0.72	−0.000486	−0.14
size	0.000000	0.96	0.000000	0.16	0.000000	0.21
log(size)	−0.000399	−1.05	−0.000470	−0.96	−0.000228	−0.33
holding.per	0.000946	3.67^{***}	0.001216	3.59^{***}	0.000846	1.76°
$\overline{R^2}$	0.095		0.089		−0.007	
F	4.342		4.014		0.829	

Table 9: Regression Results, CT Measures, Private Portfolios

Dependent variable: Average CT measure by manager, for various aggregation levels of benchmark. This table presents results from cross-sectional regressions, by manager, for private portfolios. The independent variables are portfolio specialization, portfolio size, log of portfolio size and average property holding period.

			National/Type		National/Subtype	
			Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)			0.002475	0.22	0.000669	0.05
special.			−0.001253	−0.33	−0.001063	−0.23
size			0.000000	−0.71	0.000000	−0.77
log(size)			−0.000022	−0.03	0.000102	0.12
holding.per			−0.000194	−1.98°	−0.000201	−1.91°
$\overline{R}^2$			0.037		0.028	
F			1.858		1.659	
	Regional		Regional/Type		Regional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.018745	−1.50	−0.017807	−1.22	−0.012699	−0.77
spec.	0.009159	2.31*	0.007683	1.69°	0.005260	1.01
size	0.000000	−0.86	0.000000	−1.06	0.000000	−0.94
log(size)	0.001069	1.34	0.001189	1.22	0.000921	0.83
holding.per	−0.000235	−2.75**	−0.000258	−2.45*	−0.000255	−2.30*
$\overline{R}^2$	0.087		0.052		0.037	
F	3.135		2.231		1.869	
	Divisional		Divisional/Type		Divisional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.014409	−1.10	−0.017634	−1.22	−0.010733	−0.66
spec.	0.006783	1.63	0.006728	1.49	0.003727	0.73
size	0.000000	−0.83	0.000000	−1.19	0.000000	−0.99
log(size)	0.000825	0.99	0.001163	1.20	0.000768	0.71
holding.per	−0.000206	−2.31*	−0.000224	−2.14*	−0.000213	−1.97°
$\overline{R}^2$	0.047		0.035		0.021	
F	2.115		1.811		1.485	
	State		State/Type		State/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.012809	−0.92	−0.014162	−0.97	−0.018094	−1.15
spec.	0.005090	1.15	0.003731	0.82	0.005887	1.17
size	0.000000	−0.81	0.000000	−1.13	0.000000	−1.12
log(size)	0.000750	0.84	0.000927	0.95	0.001162	1.10
holding.per	−0.000183	−1.92°	−0.000179	−1.70°	−0.000194	−1.83°
$\overline{R}^2$	0.015		0.004		0.01	
F	1.352		1.097		1.227	
	CBSA		CBSA/Type		CBSA/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.014794	−1.00	−0.024824	−1.59	−0.006070	−0.34
spec.	0.005895	1.25	0.006792	1.39	0.003862	0.66
size	0.000000	−0.72	0.000000	−1.23	0.000000	−0.22
log(size)	0.000947	1.00	0.001620	1.55	0.000184	0.15
holding.per	−0.000252	−2.50*	−0.000221	−1.96°	−0.000083	−0.70
$\overline{R}^2$	0.036		0.011		−0.027	
F	1.849		1.257		0.443	