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

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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. Portfolio managers exhibit substantial variation in their ability to successfully select investments, with nearly half exhibiting positive selectivity, with a substantial fraction of the distribution doing so significantly. Both timing and especially selectivity performance exhibits significant persistence in the center of the performance distributions, but not at the top. Due to the nature of the performance distributions of the two measures, this finding leads to possible portfolio allocation strategies to capture selectivity only, since little persistence is found among mangers that realize positive timing. Managerial ability to time markets has a positive concave relationship with portfolio size and a negative relationship with portfolio turnover. Ability to select investment classes has a positive relationship with portfolio turnover, but individual skill seems very important for asset selection.

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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 pick 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 suggest that managers possess little ability to generate consistent abnormal returns. 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 for characterizing trading strategies in the real estate market, in that it provides a method for examining whether and how informational advantages are exploited. In the mutual fund literature, results from such decomposition point to some limited degree of ability on the part of managers in terms of *selectivity*, but nearly no ability in terms of *timing* (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. As benchmarks, we employ property portfolio index returns at a CBSA level, a state level, a divisional level, a regional level and at the whole national level, each interacted with property type classes. 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. Both private and public managers, on the other hand, exhibit substantial dispersion in their characteristic selectivity ability, and in the top half of the distribution, appear to positively enhance returns through investment selection, with a considerable fraction doing so statistically significantly.

To analyze the extent to which managerial timing- and selectivity-based performance is persistent, we examine autocorrelations of the characteristic timing and selectivity measures, the persistence of a manager's timing and selectivity rankings through time, as well as manager permanence in the top of the distribution through time. We find strong positive persistence in managerial market timing ability, for lags of up to two years, which then reverts over a three year horizon. This persistence in timing ability is stronger when timing ability is measured using benchmarks with a higher level of aggregation. Persistence is weaker, however, when measured using rank persistence measures, where we find widespread persistence only over one year. However, given the low mean and median timing performance, investing based on these autocorrelations would not necessarily lead to an investment allocation to a manager who has overall *positive* timing ability. We therefore proceed to examine the permanence of managers in the top quartile and the top decile of performance (where we observe positive performance) over time. We find the degrees of permanence to be very low, with typically about one quarter of top-quartile managers remaining in the top quartile over multiple years, and only around one tenth of top-decile managers remaining in the top decile for multiple years. Thus, it would be difficult to form an investment strategy that allocates capital to a manager with positive timing ability, using the information available from past returns.

Similarly, we find strong positive persistence in characteristic selectivity ability, especially in rankings, over a one- and two-year horizon. this persistence is present for benchmarks with a high level of aggregation even over a three-year horizon. Unlike with timing, however, since the mean and median selectivity performance is close to zero, these results do suggest a capital allocation strategy for investors, as the selectivity performance persistence implies that past positive selection will be followed by positive selection. While the degree of permanence in the top market quartile and decile are also low for selectivity ability, this poses less of a problem for formulating an investment strategy, as efficient capital allocations can be made by an investor based on significantly positive autocorrelations alone. Thus, our results suggest that in an inefficient market such as real estate, in which transactions are costly and difficult, specialized managers may generate value primarily through asset selection, and efficient portfolio allocations may be made by investors based on this knowledge, using information on past performance.

Finally, we perform a cross-sectional analysis in an attempt to characterize the types of portfolios that are associated with higher characteristic timing or selectivity ability. When we regress timing and selectivity on manager and portfolio characteristics, we find a concave relationship between portfolio size and measure of characteristics timing, but little relationship between portfolio size and characteristic selectivity, for both private and public managers. Specialization, at both the property type and across geographies, exhibits no significant relationship to either characteristic timing or selectivity for either set of managers. In contrast, for both public and private managers, we find a significant *negative* relationship between portfolio turnover and characteristic timing ability, and a significant *positive* relationship between portfolio turnover and characteristic selectivity 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

[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

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 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 such 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 contributes to the debate about the relative efficiency of public versus private entities. We find little distinction in the ability of the two types of entity to create economic value in this market, and therefore no clear distinction in relative efficiency between them.

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

indirect public-market related measures to infer information about the more inefficient private market.

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 month 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 National Property Index (NPI) total return indices. For example, if a manager owned an office building in Chicago's Central Business District (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, $R_{j,t}$ would be the return to stock (or 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 (or properties) that outperform his or her benchmark portfolio. As with the CT measure, DGTW re-compute this measure every time period, as do we.

Due to the nature of property data, however, we make a more substantial modification to this measure. The need to do this arises from the lack of reliable price or return series for the individual properties held by the managers in our data. Given that these properties are not traded while they are held in a manager's portfolio, they are also not priced. For REITs, this limitation is absolute, as these firms also do not disclose appraisals of the properties in their portfolio. While NCREIF members do disclose periodic appraisals, using these would prevent us from conducting a clean comparison between our two types of entity.[4] Thus, instead of actual property prices, we use the total return for the NPI for the same CBSA and property type as the property itself for $R_{j,t}$.[5] Economically, therefore, our modified selectivity measure indicates a manager's ability to select outperforming sub-markets, rather than specific outperforming assets. If the manager can do this over his entire portfolio, this manager has selective abilities, and the weighted average of outperformances (and therefore CS_t) in a given quarter would be positive.

Once again, we compute these measures for all degrees of specialization of the benchmark

[4]Furthermore, it is widely documented that such appraisals are problematic in that they suffer from *appraisal smoothing.*

[5]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. While total return for the NPI for the same CBSA and property subtype would seem to be a closer proxy, this return series is very often unavailable, because the number of properties reporting to NCREIF is below our threshold of ten.

portfolio. Continuing the previous example, we would proxy for the return from holding a Chicago CBD office building by using returns to the overall Chicago Office market. Each of these quarterly returns becomes $R_{j,t}$. From this, in a first run, we then subtract the overall Chicago commercial property market return in the same quarter, to show whether the manager's selection of office property outperformed. In the next run, we would compare the local return to the return to the Illinois CBD Office market, then the Illinois Office market, then the overall Illinois market, and so forth, once again using all levels of aggregation or specialization, geographically and by type or subtype. Since the CBSA/Type portfolio serves as a property return proxy, 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 measures, we proceed to investigating the time-series persistence of any outperformance we might find. Should managerial ability in fact be persistent, a potential investor's capital allocation decision would be simplified, as she can simply allocate money to portfolios which have exhibited positive outperformance with respect to our two measures in the past. In order to investigate this, we first estimate auto-correlations of annualized CT and CS measures over a panel of these measures by manager over time. We use one- two- and three-year lags. We then rank managers according to their annualized CT and CS measure each year, and estimate autocorrelations of ranks. Further, we measure transitional statistics, which show permanence of managers in the top 25 percent and top 10 percent of the performance distribution of managers, over time. We do this simply by calculating what percentage of those managers who were in the top quartile or top decile in the past, are still there. Again, we do this based on annualized CT and CS, and measure these statistics over one- two- and three-year horizons.

We then proceed to investigate which managers are more or less successful, as a function of various observable portfolio characteristics. We do this by running panel regressions as follows:

$$CT_{i,t} = \alpha + \beta_1 geo.spec_{i,t} + \beta_2 type.spec_{i,t} + \beta_3 size_{i,t} + \beta_4 log(size_{i,t}) + \beta_5 turnover_{i,t} + \epsilon_{i,t} \quad (3)$$

$$CS_{i,t} = \alpha + \beta_1 geo.spec_{i,t} + \beta_2 type.spec_{i,t} + \beta_3 size_{i,t} + \beta_4 log(size_{i,t}) + \beta_5 turnover_{i,t} + \epsilon_{i,t} \quad (4)$$

In the equations above, the dependent variables are, for each manager in each quarter, the current CT measure and the current CS measure, respectively. For the independent variables, in order to allow for slow effects of a set of characteristics of a particular portfolio strategy, we use one-year moving averages or trailing sums of each of the time series employed.

The independent variable $size_{i,t}$ is manager i's average portfolio size in square feet between quarter $t-3$ and t. $log(size_{i,t})$ is the natural logarithm of the same moving average series. $turnover_{i,t}$ shows fractional portfolio turnover during the previous year and is defined analogously to the *turnover* variable in CRSP's Survivorship-Bias Free Mutual Fund Database. Specifically, in our case we define this measure as

$$turnover_{i,t} = \frac{\sum_{i=0}^{3} b_{t-i}}{\sum_{i=0}^{3} size_{t-i}/4} \quad (5)$$

where $b_\tau = min(sqf.bought_\tau, sqf.sold_\tau)$ or the minimum of square footage bought and square footage sold at time τ. The *turnover* measure, thus, is defined as the total square feet turned over during the previous year, as a fraction of the average portfolio size during that same time period.

The two variables $geo.spec_{i,t}$ and $type.spec_{i,t}$, which measure the level of geographic and property type specialization of a manager's portfolio, respectively, are computed as a Hirschman-

Herfindahl Index, defined as follows:

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

Here $w_{s,t}$ 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 that submarket). For geographic specialization, each CBSA constitutes a submarket. For type specialization, each property type constitutes a submarket. Both these measures will be equal to 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. In line with the other independent variables, $geo.spec_{i,t}$ and $type.spec_{i,t}$ are then defined as moving averages from quarter $t-3$ to quarter t of the respective series of $H_{i,t}$.

We estimate a version of Equations 3 and 4 for performance measures computed with respect to benchmarks at all the levels of aggregation we employ. We also estimate separate regressions for public and private portfolios. All regressions contain year fixed-effects and standard errors clustered by manager.

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 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 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. The statistics in this table are computed analogously to those in Table 3. That is, we first compute, for every manager in every quarter, the CS_t measure described in Equation (2). 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 CS statistic per manager. The table displays the mean, standard deviation, minimum, first quartile, median, 3rd quartile and maximum of these measures across managers. As for the CT measures, 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, here too thee distributional statistics are illustrated in Figure 3. 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 CBSA/Type level returns are used as the proxy for actual investment selection relative to the category benchmark, the table naturally omits any statistics for the CBSA/Type- or CBSA/Subtype-level benchmarks.

Both the table and the figure show that for selectivity we obtain a mean and median that is very close to zero. This means that, while about half the managers in our sample do seem to exhibit negative characteristic selection, the other half actually exhibits positive characteristic selection. This is in contrast to the results on timing, where positive performance exited only in upper outliers of the distribution. Also, unlike with timing, the position of the means and medians of the selectivity distributions are fairly homogeneous across both public and private managers, and not just across various benchmarks.

One further pattern that emerges is that at lower levels of geographic aggregation, characteristic selection ability shows more dispersion, with respect to the geographic-only benchmark than with respect to benchmarks disaggregated by both geography and property class. Consider, for example, the case of public portfolios at the State level. The distributions of all three sets of selectivity (State, State/Type, and State/Subtype) have means that are very close to zero (about four basis points per annum outperformance for State and State/Type and a half basis point for State/Subtype). Yet the standard deviation of selection by State only is about 4.5 basis points per annum, while those with respect to the benchmarks interacted with property class are about 3 basis points per annum, or two thirds as high. Similar patterns can be seen by examining the median and the inter-quartile spread. The regional, divisional, and state level results for both types of manager illustrate this pattern to some extent. This seems to suggest that selection of the right property class within geographic subdivisions is an important part of managerial value added, and that this component of ability contains a high degree of heterogeneity.

In line with our discussion of the distributions of CT measures above, we also ask whether managers are able to successfully and significantly select investment characteristics. Here too we conduct t-tests for the hypothesis that a manager has zero selection ability against the two-sided alternative, and the distributions of t-statistics from these tests are reported in Table 6. Once again, we compute each manager's CS_t in each quarter as in Equation (2) and compute a time series average over the entire activity of each manager. Then, we test the hypothesis of zero selection ability over the manager's entire period of activity. To help with interpretation, these distributions are also presented in Figure 4.

As is apparent from both the table and the figure, unlike with Characteristic Timing, the entire range of Characteristic Selectivity performances between the first and the third quartile are not statistically distinguishable from zero at the 5% significance level. However, as is apparent in Figure 4, a t-value of $+2$ is still well within the range covered by the whiskers (the same can be said about a value of -2). This means that, unlike with timing, one does not have to look for extreme positive outliers to find significant outperformance in this dimension. These results again are fairly homogeneous across benchmarks and types of manager.

Overall, these results are quite encouraging: about half of all managers create value through characteristic selection, with an appreciable amount doing so even significantly, over their period of activity. This is in sharp contrast to timing, where most managers exhibit negative performance, with only the extreme positive outliers showing significantly positive value added. This suggests that investors should look for managerial value added along the dimension of characteristic selection, as opposed to timing, as considerable ability seems to exist here.

4.3 Persistence of Timing and Selection

Having found some isolated evidence of positive timing ability, and more widespread evidence of selection ability, we now turn to the question of how to make capital allocation decisions based on these abilities. In order to do this, an investor must be able to gauge *ex ante* what a manager's abilities are, and thus, a natural starting point for this investigation is to examine whether such abilities are persistent: Does a manager who exhibited timing or selection ability in the past continue to add value along these dimensions in future years?

We begin by investigating autocorrelations in CT and CS measures for each manager over time, using panel datasets of annualized manager-by-manager CT and CS measures. Table 7 reports these results for CT measures. The table reports the mean CT over the entire panel with respect to each level of geographic and property-class aggregation, as well as one-year two-year and three-year autocorrelation of CT measure, for both public and private managers. Each correlation coefficient also includes significance stars testing a null hypothesis that the true correlation is zero, against the two-sided alternative. It is important to note that these measures indicate performance persistence only with respect to deviations from the mean. Therefore, a positive autocorrelation simply indicates persistent above-mean or below-mean performance from year to year. Given that the mean CT is negative, and given the distribution of CTs we report in the previous section, above-mean performance does not indicate actual *positive* generation of value through timing.

While the mutual fund literature finds, for the most part, no persistence in the performance of actively traded portfolios, we do find significant persistence in timing in the real estate market, for both publicly and privately held portfolios. For both types of portfolio managers, Table 7 indicates significantly positive autocorrelation over a one-year horizon. Over a two-year horizon, we also find significantly positive autocorrelation of CT values, for all but the smallest levels of aggregation

(State/Subtype, CBSA/Type and CBSA/Subtype for REITs, and State/Subtype for NCREIF managers). For a one-year horizon, the timing performance of private managers tends to have a higher autocorrelation than that of public managers (above .4 with a maximum of .4377 for the national benchmark for private managers, compared to a maximum value of .2472 for REITs). For a two-year horizon, especially for solely geographic benchmarks (i.e. not interacted with property class), public REIT managers tend to have higher autocorrelation in timing performance than private portfolio managers. Overall, autocorrelation coefficients tend to be higher (and therefore persistence tends to be stronger) when considering timing ability with respect to only a geographic benchmark, as opposed to a benchmark which interacts geography and property class.

Over a three-year horizon, however, without exception, the autocorrelation coefficients are negative and significant at least at the 1% level, and mostly at the 0.1% level, with values ranging from $-.3399$ for REITs over a national benchmark, to $-.1341$ for REITs over a State/Subtype benchmark, with most values lying between $-.2$ and $-.3$. This suggests that within three years, above-average timing will turn into below-average timing and vice versa. It therefore seems that while the timing strategies and abilities of the managers in this market do persist in the short run, they are still short-lived and followed by reversals. REIT timing seems to be slightly more variable over short horizons than private market timing, but relatively more long-lived.

Table 8 reports panel means and autocorrelations for the Characteristic Selectivity measures. First, we note that the panel means for this measure are much closer to zero than for the CT results, and therefore above-mean performance, in most cases will mean positive asset selectivity, and below-mean performance will mean negative asset selectivity. Over a one-year horizon there is strong evidence of positive persistence; all correlation coefficients are positive and significant at the 0.1% level, with the lowest coefficient value of .1807 for REITs with respect to a State/Subtype, the highest of .432 for REITs with respect to a CBSA benchmark, and most coefficient values between .2 and .4.

Over a two-year horizon, however, the evidence for persistence of selection ability is more sparse. For REITs the only significant autocorrelation coefficients are with respect to geographic benchmarks, not interacted with property class. In other words, the data shows that it is only a REIT manager's ability to select a property class investment within a certain geographic area that persists, and not any selection made based upon finer distinctions. In fact at the State/Type and State/Subtype level, significant reversals begin to show, even at the two-year horizon; these are also visible at the three-year horizon. Part of these results could be due to outliers, as can be seen when comparing these to Table 10, so these interpretations must be approached with some caution. Except for these two coefficients, neither significant persistence nor reversals exist in REIT selectivity at the three-year horizon.

For private managers, there is strongly significant persistence at the two-year level, for National and Regional benchmarks, even when interacted with property class. This diminishes when using less aggregated geographic benchmarks, with significant persistence at only the Divisional and Divisional/Type level, the State/Subtype level, and no persistence at the CBSA level. These results are consistent with a hypothesis of private investors showing the ability to make positive selections at a more coarse geographical level, with REIT investors making more targeted property-class plays. At the State level, over a three-year horizon, private investors also show significant reversals in selective ability.

Next, we examine the persistence of manager relative rankings over time, with respect to timing and selection ability. Each year, we construct a percentile rank for each manager, according to his or her realized performance with respect to timing and selectivity over the past year. We then compute autocorrelations of percentile ranks over one-, two-, and three-year horizons, as well as permanence measures, $75plus_{\tau,t}$ and $90plus_{\tau,t}$. $75plus$ indicates, out of all managers whose performance rank was at or above the 75th percentile at time τ, that fraction whose performance is still at or above the 75th percentile at time t. $90plus$ is an analogous measure for the 90th percentile. We construct these using CT and CS measures at all levels of benchmark aggregation. Given that only the top few portfolio managers in our sample show positive timing ability, the $90plus$ measure for the timing performance should be of particular interest in this study.

Table 9 shows the results for rank persistence with respect to Characteristic Timing. Similar to the persistence results for the CT measure itself, there is strong positive persistence in manager rank at the one-year horizon, for both public and private portfolios, at the higher levels of benchmark aggregation, with a top coefficient of .4715, for REITs on a national benchmark. The interpretation of these positive coefficients is that managers will not cross the median within the course of a year: above-median managers remain above-median and below-median managers remain below-median. However, unlike for the CT measure itself, the positive autocorrelation becomes much more sparse, at lower levels of aggregation; for public portfolios this begins at the Divisional/Subtype level, with only an isolated significantly positive coefficient for State, while for private portfolios this begins at the State/Type level, with only one weakly positive coefficient for CBSA. The difference between these rank correlations and the direct correlations reported in Table 7 is that the latter could be affected by outliers, while the former are robust to this. This indicates that, with few exceptions, persistence in timing ability exists primarily with respect to coarser benchmarks.

At longer time horizons, public portfolios only show weakly positive rank persistence in timing geographic benchmarks, but hardly any in timing benchmarks that interact geography with property class. In fact, at the two-year horizon, public portfolios show some degree of reversion in timing rank, when combined geography-class benchmarks are used, at a wide variety of levels of aggregation. Private portfolios show more widespread rank persistence with at least weak persistence at the two- and three-year horizon extending to the Divisional level, even when geographic benchmarks are interacted with property class. Furthermore, private managers show no significant reversion in ranks at any level.

While this degree of persistence seems encouraging for investors interested in formulating strategies for allocating capital, these correlation coefficients show primarily movements about the median, which in the case of the CT measures is negative. As is shown in Table 4, if an investor is looking for positive managerial ability, she will need to find a manager who is at the very top of the distribution. The $75plus$ and $90plus$ measures illustrate whether this is possible. The highest values of these measures, reported in Table 9 are for REITs at the National level, where for $75plus$ and $90plus$, these are .67 and .69 respectively. The latter measure, for example, indicates that 69% of managers who were ranked in the top 10% of the market the previous year, are ranked there in the current year as well. Even at a two-year and three-year horizon, these measures are .6 and .65 respectively. However, these high values are the exception rather than the rule, with the only other realizations of these two measures above .5 being for private portfolios at the National level. More typical values are between .2 and .3 for $75plus$ and between .1 and .2 (or even less than .1) for $95plus$. This indicates a high degree of turnover in terms of which managers occupy the top of the performance distribution. This means that at most levels of benchmarks, even if one finds a manager that generates positive timing over a given year, this finding is unhelpful for capital allocation decisions, in that a repeat performance is unlikely.

A slightly different picture emerges from Table 10. There appears to be somewhat widespread persistence in selectivity rank, including, with a few exceptions, at the two-year horizon, at low levels of benchmark aggregation. This is the case for both public and private portfolios here. Even at the three-year horizon, the larger levels of aggregation (National and Regional) exhibit some degree of persistence. This is in contrast to the results on persistence in selectivity itself. Once again, the difference is that these correlations are more robust to outliers. Given that the median level of selectivity is close to zero, these results are encouraging for the task of portfolio formation, as past positive performance should give some degree of confidence of such performance in the future.

While for this measure the autocorrelation coefficient itself is already informative in this respect, we also examine the $75plus$ and $90plus$ measures for selectivity rankings. The maximum values found in this table (.5 for $75plus$ for REITs at the National level and .37 for $90plus$ for private portfolios at the National level), and the typical values for these two measures are only slightly higher than those found in Table 9. Therefore, even for selectivity it seems to be the case that the top of the performance distribution has a high degree of turnover, and very little confidence can be placed into allocating money to a top manager based on past performance. However, once again, since the median CS is close to zero, the strongly positive rank-autocorrelations found in this table still facilitate finding a manager who is likely to add value along this dimension.

4.4 Timing, Selection and Portfolio Characteristics

Our final analysis is a cross-sectional analysis of characteristic timing and selectivity ability in an attempt to relate performance on these measures to various portfolio attributes, such as specialization in a particular market segment, size of the portfolio, and portfolio turnover. Can we attribute timing and selection abilities to known characteristics, or are they attributable to individual manager skill?

To get a handle on these questions, we undertake a regression analysis that relates our CT and CS measures to portfolio characteristics. We estimate the regressions separately for public and private portfolios. Tables 11, 12, 13 and 14 present estimates from manager by manager cross-sectional regressions described by Eq.s 3 and 4. 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. As dependent variables, we include the one-year moving average size of the portfolio, measured in square feet under management, the log of the portfolio size, measures of geographic and property type specialization, measured as the Hirschman-Herfindahl index by square feet under management across CBSA for geographic specialization and across property sub-type for property type specialization, as well as our measure of portfolio turnover. All our models include year fixed effects and are estimated as panel regressions with robust heteroskedasticity-consistent standard errors clustered by portfolio manager.

Tables 11 and 12 present estimates from our manager by manager panel 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 range from 0.227 to 0.551, suggesting that they are able to capture a significant portion of the variance in characteristic timing. A consistent pattern is apparent for these regression models, for both public and private managers. While specialization, both geographic and by property type, exhibits no significant relationship to characteristic timing, the size of the portfolio exhibits a positive but concave relationship to timing ability, and high portfolio turnover is associated with lower levels of characteristic timing performance.

Tables 13 and 14 present estimates from our manager by manager panel regressions where the dependent variable is the manager's characteristic selectivity performance measure. In general, the models appear to have low explanatory power relative to the models for CT described above, 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 portfolio turnover are not significantly correlated with private manager's selection ability, while higher turnover for public portfolio managers is associated with higher levels of characteristic selectivity performance. Both the low adjusted-R^2s for the models and the lack of systematic significance on the characteristic coefficients 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 some persistence in timing and selectivity performance, a finding which aids efficient portfolio allocation in order to profit from managers' selection abilities. Managerial ability to time markets has a positive concave relationship with portfolio size and a negative relationship with portfolio turnover. Ability to select investment classes has a positive relationship with portfolio turnover, but individual skill seems very important for asset selection.

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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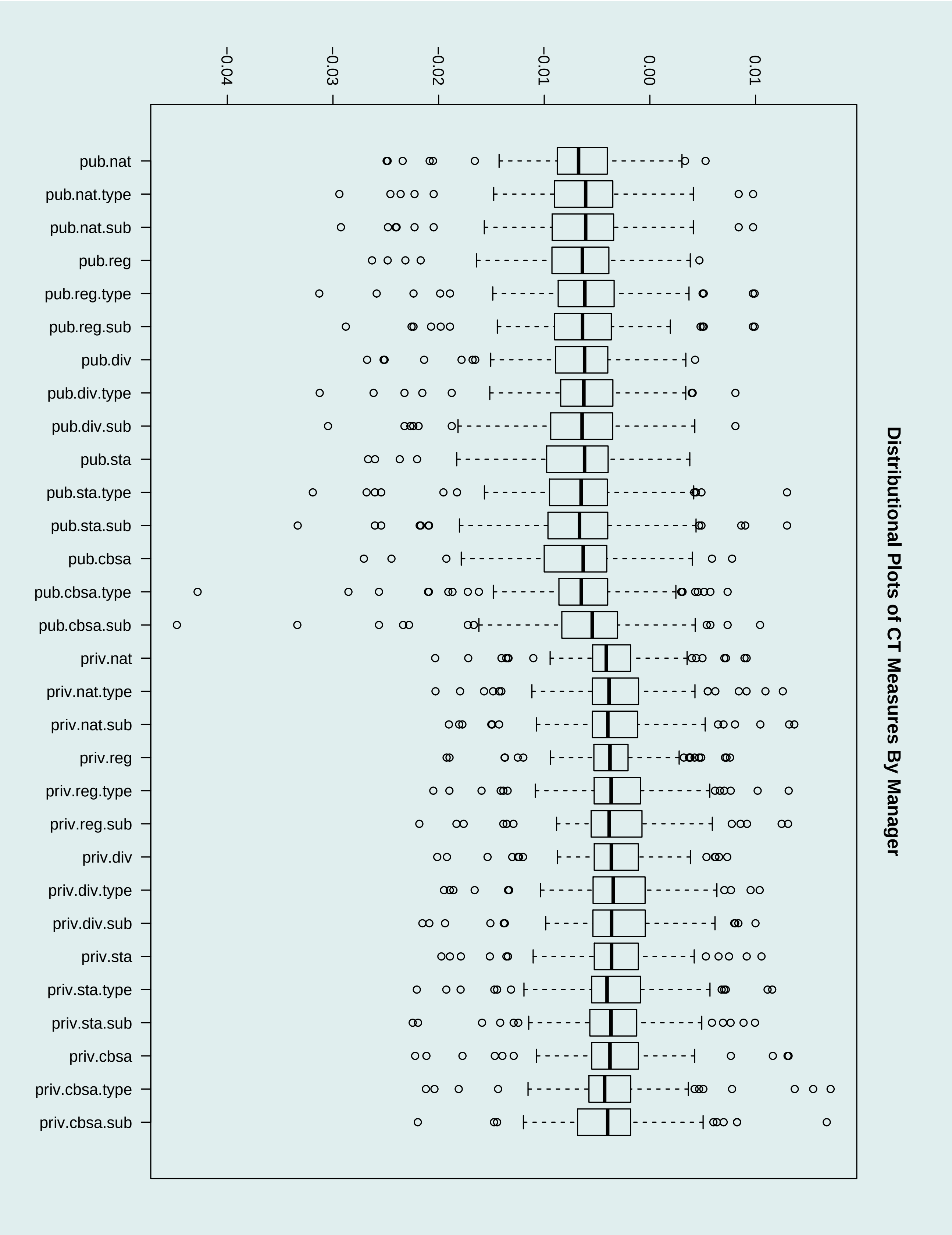

Figure 1: This figure shows box-and-whisker diagrams comparing the cross-sectional distributions of CT measures obtained by managers with respect to the various aggregation levels of benchmarks. The data presented includes REIT managers (starting with *pub*) and private managers (starting with *priv*).

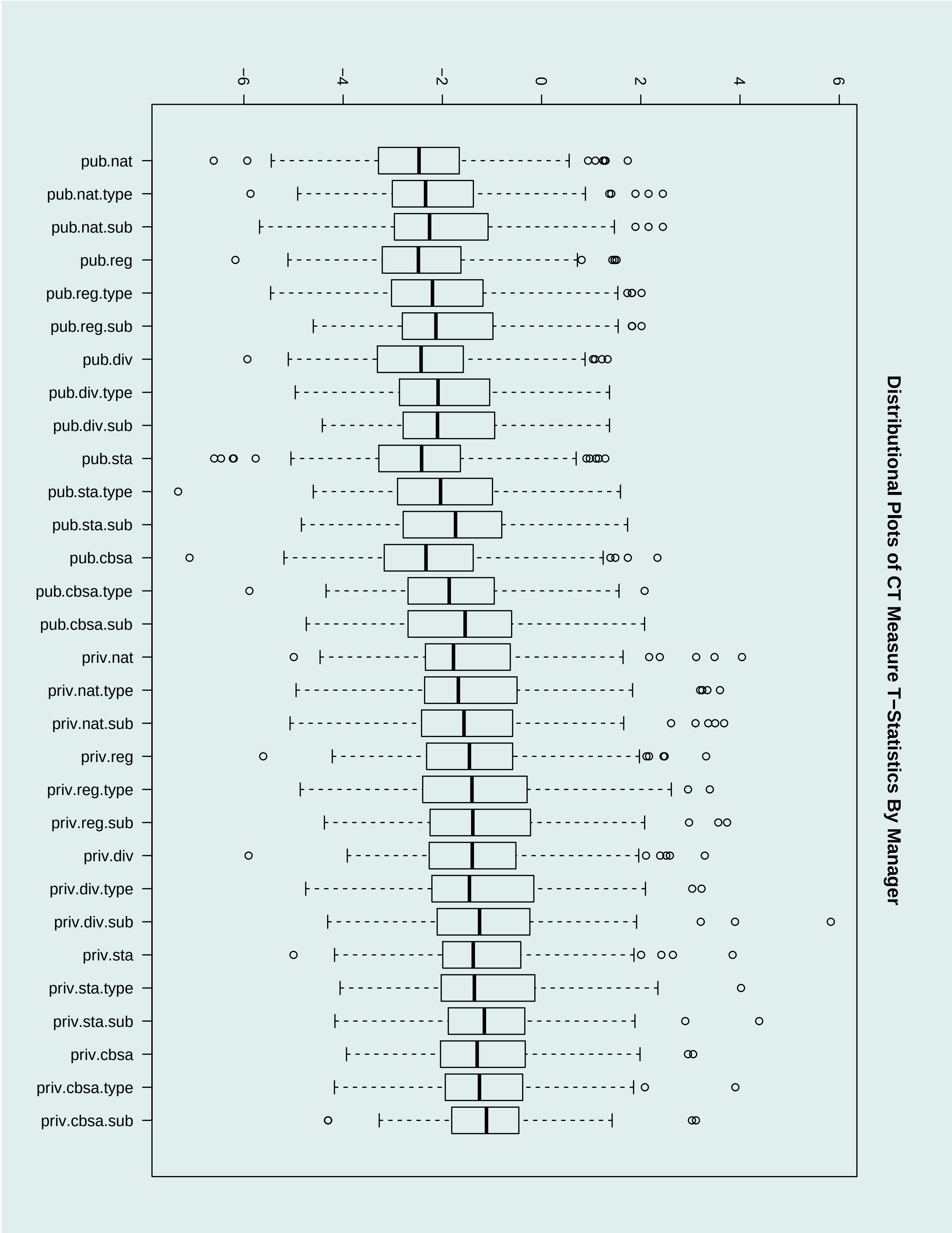

Figure 2: This figure shows box-and-whisker diagrams comparing the cross-sectional distributions of the t-statistic that a manager's CT-measure is different from zero. The data presented includes REIT managers (starting with *pub*) and private managers (starting with *priv*).

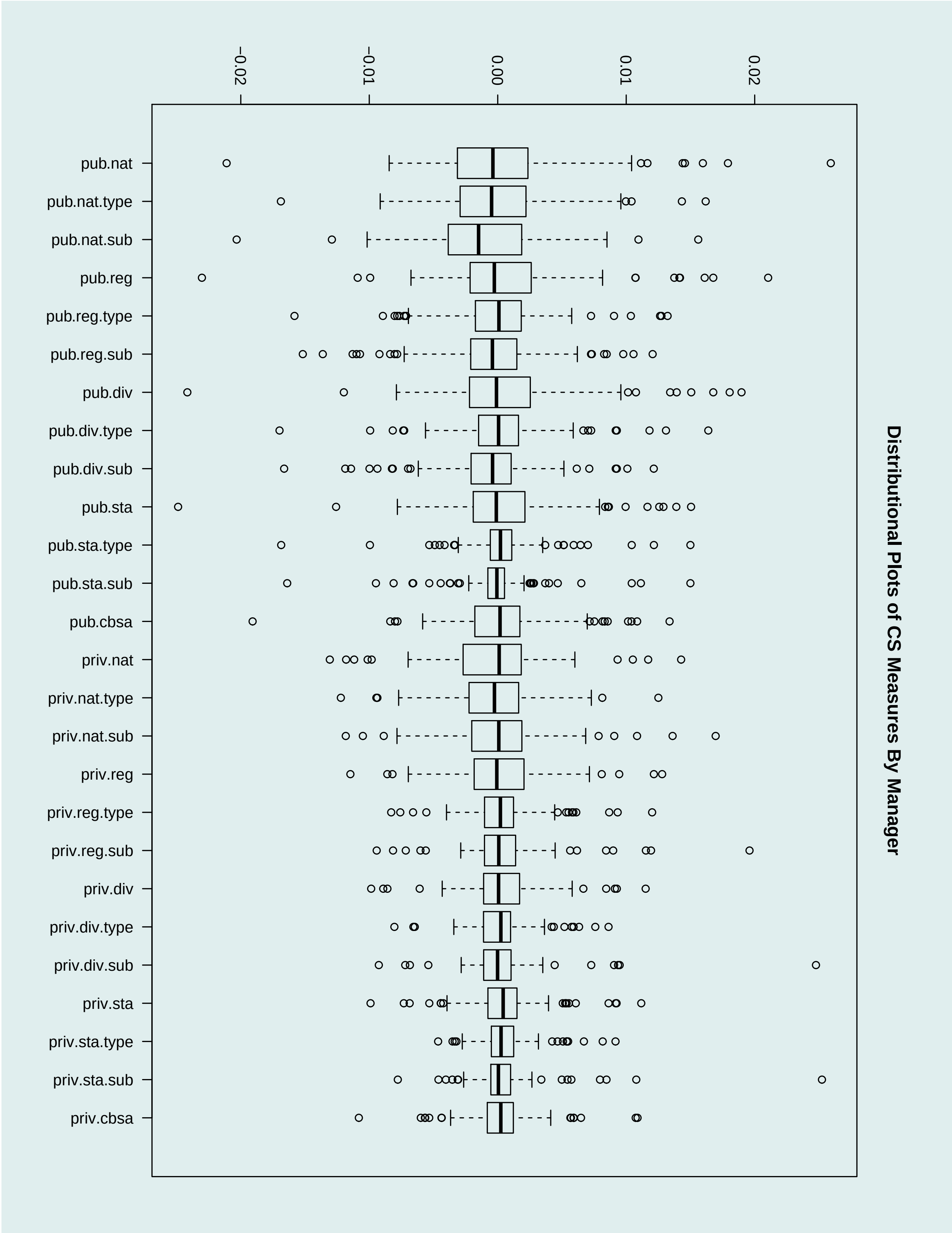

Figure 3: This figure shows box-and-whisker diagrams comparing the cross-sectional distributions of CS measures obtained by managers with respect to the various aggregation levels of benchmarks. The data presented includes REIT managers (starting with *pub*) and private managers (starting with *priv*).

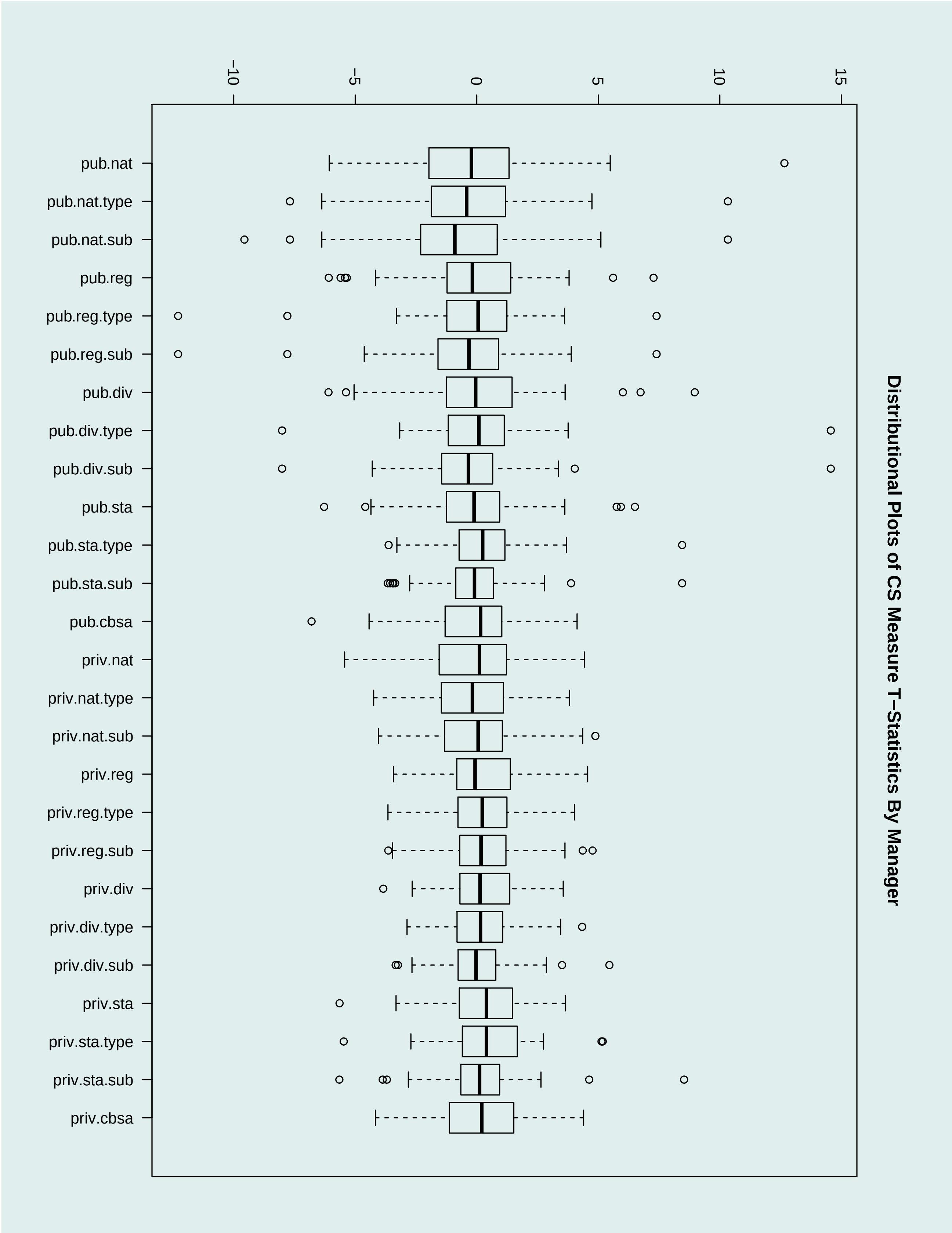

Figure 4: This figure shows box-and-whisker diagrams comparing the cross-sectional distributions of the t-statistic that a manager's CS-measure is different from zero. The data presented includes REIT managers (starting with *pub*) and private managers (starting with *priv*).

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)	3.75	2.14	2.08	3.50	5.32
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: Means.

This table presents distributional characteristics across managers, for time-series means of quarterly Characteristic-Selectivity (CS) 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 CS measure over 12 quarters or more.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
Mean	0.00021	$-3.9e-05$	-0.000879	-0.000217	-0.000192	$9e-05$
StdDev	0.00556	0.00452	0.004705	0.004419	0.003938	0.00436
Min.	-0.01969	-0.01568	-0.019044	-0.013070	-0.012212	-0.01183
1st Qu.	-0.00312	-0.00284	-0.003819	-0.002695	-0.002234	-0.00202
Median	-0.00029	-0.00044	-0.001458	0.000113	-0.000257	$8.3e-05$
3rd Qu.	0.00243	0.00222	0.001897	0.001829	0.001628	0.00188
Max.	0.02629	0.01626	0.015667	0.014275	0.012503	0.01696
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
Mean	0.000644	0.000297	-0.000451	0.000215	0.000409	0.000523
StdDev	0.005133	0.003766	0.004125	0.003701	0.003057	0.003749
Min.	-0.021777	-0.014922	-0.014332	-0.011470	-0.008293	-0.009422
1st Qu.	-0.002089	-0.001718	-0.002079	-0.001836	-0.001027	-0.001032
Median	-0.000215	0.000166	-0.000395	$-7.2e-05$	0.000207	$8.2e-05$
3rd Qu.	0.002652	0.001871	0.001567	0.002044	0.001228	0.001392
Max.	0.021393	0.013528	0.012119	0.012797	0.012018	0.019599
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
Mean	0.000616	0.000355	-0.000607	0.000224	$3e-04$	0.000336
StdDev	0.005166	0.003666	0.003756	0.003373	0.002561	0.00371
Min.	-0.022997	-0.016104	-0.015745	-0.00985	-0.008044	-0.009256
1st Qu.	-0.002115	-0.001413	-0.002041	-0.001098	-0.001106	-0.00109
Median	$1e-06$	0.000133	-0.000391	$6.6e-05$	0.000243	$-1.2e-05$
3rd Qu.	0.002579	0.001720	0.001101	0.0017	0.000998	0.001026
Max.	0.019436	0.016825	0.012204	0.011513	0.008624	0.02477
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
Mean	0.000397	0.000406	$-8e-05$	0.000499	0.000643	0.000554
StdDev	0.004566	0.003036	0.003038	0.003273	0.002257	0.003551
Min.	-0.023742	-0.015998	-0.015572	-0.0099	-0.00464	-0.007778
1st Qu.	-0.001777	-0.000549	-0.000736	-0.000763	-0.000497	-0.000522
Median	$-8.5e-05$	0.000238	$-3.8e-05$	0.000422	0.000258	$5.1e-05$
3rd Qu.	0.002183	0.001107	0.000543	0.001498	0.001242	0.000995
Max.	0.016057	0.015036	0.015036	0.011172	0.009167	0.025236
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
Mean	0.000301			0.000207		
StdDev	0.003843			0.003071		
Min.	-0.018732			-0.01081		
1st Qu.	-0.001772			-0.000813		
Median	0.000184			0.00024		
3rd Qu.	0.001755			0.001215		
Max.	0.013946			0.010883		

Table 6: Characteristic-Selectivity Measures: t-statistics.

This table presents distributional characteristics across managers, for t-statistics testing the hypothesis $H_o : CS = 0$ against the two-sided alternative, over a manager's time series of quarterly CS measure observations. 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. We include only managers for whom we can compute a CS measure over 12 quarters or more.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
Mean	−0.3132	−0.4167	−0.7994	−0.1962	−0.2246	−0.0860
Min.	−6.0617	−7.6777	−9.5511	−5.4368	−4.2436	−4.0436
1st Qu.	−1.9462	−1.8490	−2.2835	−1.5470	−1.4559	−1.3222
Median	−0.2001	−0.3699	−0.8661	0.1094	−0.1802	0.0571
3rd Qu.	1.3393	1.2519	0.8956	1.2221	1.0981	1.0538
Max.	12.6675	10.3411	10.3411	4.4268	3.8182	4.8790
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
Mean	0.0525	−0.0238	−0.3733	0.1812	0.1929	0.1850
Min.	−6.0682	−12.279	−12.279	−3.4260	−3.6533	−3.6387
1st Qu.	−1.1960	−1.2178	−1.5090	−0.8204	−0.7736	−0.698
Median	−0.1683	0.1008	−0.3088	−0.0695	0.2261	0.1757
3rd Qu.	1.4501	1.2700	0.9276	1.3815	1.2416	1.2001
Max.	7.2861	7.4061	7.4061	4.5613	4.0230	4.7634
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
Mean	0.0579	0.1617	−0.2212	0.1824	0.1360	0.0267
Min.	−6.0761	−7.9900	−7.9900	−3.8451	−2.8688	−3.3372
1st Qu.	−1.2191	−1.1396	−1.4167	−0.6925	−0.8118	−0.7408
Median	0.0004	0.1206	−0.3158	0.1352	0.1534	−0.0274
3rd Qu.	1.4843	1.1433	0.6817	1.3581	1.0698	0.7823
Max.	8.9806	14.5742	14.5742	3.5579	4.3354	5.4561
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
Mean	0.0400	0.7350	0.4730	0.2984	0.3752	0.1411
Min.	−6.2703	−3.6071	−3.6455	−5.6448	−5.4745	−5.6528
1st Qu.	−1.2022	−0.7069	−0.8410	−0.7184	−0.5930	−0.6449
Median	−0.0840	0.2848	−0.0454	0.3991	0.4004	0.1161
3rd Qu.	0.9880	1.1857	0.7334	1.4693	1.6686	0.9416
Max.	6.5229	69.2093	69.2093	3.6546	5.1819	8.5298
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
Mean	−0.0073			0.1693		
Min.	−6.7894			−4.1684		
1st Qu.	−1.2902			−1.1262		
Median	0.1744			0.2069		
3rd Qu.	1.0555			1.5242		
Max.	4.1349			4.3947		

Table 7: Characteristic-Timing Measures: Persistence

This table illustrates persistence of managers' CT performance through time. From a panel dataset, we annualize the quarterly CT measure for each manager and then we compute the overall mean, as well as one-year, two-year, and three-year autocorrelations of annual CT.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
Mean	−0.02626	−0.02504	−0.02564	−0.02025	−0.01997	−0.01971
$\rho_{t,t-1}$	0.2472***	0.2134***	0.179***	0.4377***	0.4297***	0.4364***
$\rho_{t,t-2}$	0.2135***	0.1599***	0.1311***	0.1213***	0.1227***	0.1341***
$\rho_{t,t-3}$	−0.3399***	−0.2789***	−0.2945***	−0.2094***	−0.2642***	−0.2342***
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
Mean	−0.02566	−0.02462	−0.0254	−0.01986	−0.01948	−0.01924
$\rho_{t,t-1}$	0.2377***	0.1879***	0.1045**	0.4201***	0.422***	0.4006***
$\rho_{t,t-2}$	0.2035***	0.128***	0.1128**	0.1047**	0.1161***	0.1169***
$\rho_{t,t-3}$	−0.3232***	−0.2433***	−0.2721***	−0.196***	−0.2266***	−0.2024***
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
Mean	−0.02562	−0.0246	−0.0257	−0.01961	−0.01904	−0.0188
$\rho_{t,t-1}$	0.2379***	0.1719***	0.1047**	0.3986***	0.3938***	0.3635***
$\rho_{t,t-2}$	0.2034***	0.1237***	0.0661°	0.1182***	0.1238***	0.1302***
$\rho_{t,t-3}$	−0.3156***	−0.2305***	−0.2046***	−0.1851***	−0.2223***	−0.2029***
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
Mean	−0.02579	−0.02521	−0.02539	−0.01914	−0.0189	−0.01919
$\rho_{t,t-1}$	0.1911***	0.1196***	0.0825*	0.3877***	0.3329***	0.2729***
$\rho_{t,t-2}$	0.2173***	0.1396***	0.0597	0.0965**	0.0983**	0.0537
$\rho_{t,t-3}$	−0.2454***	−0.184***	−0.1341**	−0.1571***	−0.2007***	−0.2237***
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
Mean	−0.02585	−0.02457	−0.02278	−0.01906	−0.01892	−0.01921
$\rho_{t,t-1}$	0.1346***	0.0587°	0.0348	0.2999***	0.2197***	0.224***
$\rho_{t,t-2}$	0.156***	0.0386	−0.0054	0.0653°	0.1005**	0.103**
$\rho_{t,t-3}$	−0.2121***	−0.2327***	−0.1555**	−0.1638***	−0.2029***	−0.1647***

Table 8: Characteristic-Selectivity Measures: Persistence

This table illustrates persistence of managers' CS performance through time. From a panel dataset, we annualize the quarterly CS measure for each manager and then we compute the overall mean, as well as one-year, two-year, and three-year autocorrelations of annual CS.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
Mean	−0.00101	−0.00158	−0.00448	−0.00093	−0.00126	−0.00089
$\rho_{t,t-1}$	0.3361***	0.2267***	0.202***	0.4064***	0.3533***	0.3943***
$\rho_{t,t-2}$	0.0442	0.007	−0.0082	0.1748***	0.1754***	0.2279***
$\rho_{t,t-3}$	−0.0281	0.0159	0.0114	0.0506	0.0756*	0.0475
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
Mean	0.0014	0.0001	−0.00249	0.00075	0.00055	0.00071
$\rho_{t,t-1}$	0.3576***	0.1812***	0.2103***	0.3848***	0.2444***	0.3293***
$\rho_{t,t-2}$	0.0967**	0.0045	0.0312	0.1416***	0.1143**	0.1662***
$\rho_{t,t-3}$	−0.0034	−0.0123	0.0214	−0.022	0.0133	−0.0227
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
Mean	0.00121	−0.00016	−0.00333	0.00056	0.00018	0.00007
$\rho_{t,t-1}$	0.3815***	0.2209***	0.2106***	0.3431***	0.2189***	0.3061***
$\rho_{t,t-2}$	0.1145***	−0.0255	−0.0205	0.1021**	0.0301	0.1093**
$\rho_{t,t-3}$	0.0014	−0.0331	0.0266	−0.0513	−0.0216	−0.0526
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
Mean	0.00119	0.0008	−0.00115	0.00163	0.00114	0.00064
$\rho_{t,t-1}$	0.3735***	0.1864***	0.1807***	0.314***	0.2062***	0.3413***
$\rho_{t,t-2}$	0.0949**	−0.0789*	−0.1327***	0.0357	−0.0196	0.0807*
$\rho_{t,t-3}$	−0.0345	−0.0902*	−0.1172**	−0.0727°	−0.0789*	−0.0813*
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
Mean	0.00106			0.00079		
$\rho_{t,t-1}$	0.432***			0.2777***		
$\rho_{t,t-2}$	0.174***			−0.008		
$\rho_{t,t-3}$	−0.0124			−0.0516		

Table 9: Characteristic-Timing Measures: Rank Persistence

This table shows the persistence of relative rankings of managers, according to their CT measure. Each year, we rank managers according to their realized Characteristic-Timing performance. $\rho_{t,\tau}$ shows the correlation between a manager's rank at time τ and at time t. $75plus$ and $90plus$ show permanence above the 75th and 90th percentile. Specifically, $75plus_{\tau,t}$ shows the fraction of all managers whose performance was at or above the 75th percentile at time τ, whose performance is still at or above the 75th percentile at time t. $90plus$ shows the analogous statistic for the 90th percentile.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
$\rho_{t,t-1}$	0.4715***	0.2416***	0.171***	0.3705***	0.2459***	0.2321***
$75plus_{t-1,t}$	0.67	0.4	0.34	0.54	0.36	0.36
$90plus_{t-1,t}$	0.69	0.31	0.11	0.51	0.13	0.18
$\rho_{t,t-2}$	0.3447***	−0.086*	−0.0603°	0.133***	0.1095**	0.1004**
$75plus_{t-2,t}$	0.6	0.25	0.24	0.38	0.31	0.24
$90plus_{t-2,t}$	0.65	0.23	0.18	0.36	0.1	0.09
$\rho_{t,t-3}$	0.2754***	0.0297	−0.0049	0.1525***	0.1202***	0.0967**
$75plus_{t-3,t}$	0.6	0.32	0.28	0.4	0.28	0.3
$90plus_{t-3,t}$	0.65	0.14	0.07	0.34	0.12	0.06
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
$\rho_{t,t-1}$	0.1278***	0.1333***	0.0577°	0.249***	0.187***	0.174***
$75plus_{t-1,t}$	0.24	0.34	0.27	0.32	0.31	0.29
$90plus_{t-1,t}$	0.13	0.11	0.1	0.24	0.14	0.12
$\rho_{t,t-2}$	0.0911*	−0.0677°	−0.0681°	0.0374	0.0855*	0.058°
$75plus_{t-2,t}$	0.33	0.24	0.22	0.25	0.28	0.27
$90plus_{t-2,t}$	0.22	0.13	0.16	0.14	0.1	0.12
$\rho_{t,t-3}$	0.1192**	−0.0028	−0.0469	0.1175***	0.093**	0.0809*
$75plus_{t-3,t}$	0.29	0.28	0.22	0.29	0.28	0.24
$90plus_{t-3,t}$	0.26	0.2	0.1	0.13	0.12	0.06
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
$\rho_{t,t-1}$	0.1112***	0.1083***	0.0528	0.2315***	0.1343***	0.0864**
$75plus_{t-1,t}$	0.25	0.31	0.29	0.34	0.31	0.28
$90plus_{t-1,t}$	0.14	0.11	0.16	0.17	0.11	0.09
$\rho_{t,t-2}$	0.0661°	−0.0771*	−0.0926*	0.0238	0.0701*	0.0612°
$75plus_{t-2,t}$	0.29	0.23	0.24	0.25	0.23	0.28
$90plus_{t-2,t}$	0.08	0.14	0.13	0.11	0.18	0.16
$\rho_{t,t-3}$	0.1502***	−0.0143	0.0042	0.0894*	0.0711*	0.0226
$75plus_{t-3,t}$	0.38	0.25	0.25	0.28	0.24	0.25
$90plus_{t-3,t}$	0.26	0.2	0.09	0.18	0.12	0.1
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
$\rho_{t,t-1}$	0.0664*	−0.0098	0.0124	0.1091***	0.013	0.0486
$75plus_{t-1,t}$	0.22	0.27	0.28	0.26	0.23	0.23
$90plus_{t-1,t}$	0.09	0.13	0.18	0.15	0.09	0.1
$\rho_{t,t-2}$	0.1077**	0.0192	−0.0801*	0.0669*	0.0559°	0.0611°
$75plus_{t-2,t}$	0.31	0.24	0.25	0.27	0.28	0.28
$90plus_{t-2,t}$	0.08	0.19	0.15	0.15	0.13	0.13
$\rho_{t,t-3}$	0.0565	0.0422	0.0991*	0.1177***	0.0509	−0.002
$75plus_{t-3,t}$	0.32	0.31	0.28	0.29	0.23	0.25
$90plus_{t-3,t}$	0.12	0.12	0.17	0.11	0.11	0.07
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
$\rho_{t,t-1}$	−0.0093	−0.0395	−0.0028	0.0564°	−0.0013	0.043
$75plus_{t-1,t}$	0.23	0.24	0.25	0.29	0.24	0.25
$90plus_{t-1,t}$	0.09	0.14	0.16	0.13	0.06	0.08
$\rho_{t,t-2}$	0.0497	−0.0774*	−0.1352**	0.0465	0.0398	0.0678°
$75plus_{t-2,t}$	0.3	0.26	0.19	0.26	0.28	0.28
$90plus_{t-2,t}$	0.11	0.09	0.09	0.16	0.14	0.13
$\rho_{t,t-3}$	0.0786*	0.0532	0.01	0.0871*	0.0258	0.0364
$75plus_{t-3,t}$	0.27	0.27	0.27	0.3	0.26	0.27
$90plus_{t-3,t}$	0.17	0.18	0.15	0.12	0.08	0.14

Table 10: Characteristic-Selectivity Measures: Rank Persistence

This table shows the persistence of relative rankings of managers, according to their CS measure. Each year, we rank managers according to their realized Characteristic-Selectivity performance. $\rho_{t,\tau}$ shows the correlation between a manager's rank at time τ and at time t. $75plus$ and $90plus$ show permanence above the 75th and 90th percentile. Specifically, $75plus_{\tau,t}$ shows the fraction of all managers whose performance was at or above the 75th percentile at time τ, whose performance is still at or above the 75th percentile at time t. $90plus$ shows the analogous statistic for the 90th percentile.

	REITs			**NCREIF Private**		
	National	National/Type	National/Subtype	National	National/Type	National/Subtype
$\rho_{t,t-1}$	0.4107***	0.3788***	0.3568***	0.4379***	0.3821***	0.3983***
$75plus_{t-1,t}$	0.5	0.43	0.41	0.44	0.42	0.46
$90plus_{t-1,t}$	0.29	0.27	0.23	0.37	0.31	0.32
$\rho_{t,t-2}$	0.1861***	0.2138***	0.2215***	0.2335***	0.1756***	0.2106***
$75plus_{t-2,t}$	0.36	0.38	0.36	0.36	0.3	0.31
$90plus_{t-2,t}$	0.19	0.19	0.25	0.26	0.16	0.24
$\rho_{t,t-3}$	0.0673°	0.1845***	0.1531***	0.0894*	0.1066**	0.0773*
$75plus_{t-3,t}$	0.33	0.36	0.34	0.3	0.29	0.27
$90plus_{t-3,t}$	0.19	0.16	0.12	0.15	0.13	0.15
	Regional	Regional/Type	Regional/Subtype	Regional	Regional/Type	Regional/Subtype
$\rho_{t,t-1}$	0.3469***	0.2577***	0.2747***	0.4129***	0.3167***	0.324***
$75plus_{t-1,t}$	0.46	0.39	0.43	0.43	0.46	0.41
$90plus_{t-1,t}$	0.3	0.2	0.25	0.3	0.23	0.24
$\rho_{t,t-2}$	0.1603***	0.1093**	0.1575***	0.1991***	0.1355***	0.1356***
$75plus_{t-2,t}$	0.32	0.31	0.32	0.38	0.33	0.31
$90plus_{t-2,t}$	0.17	0.19	0.19	0.15	0.19	0.13
$\rho_{t,t-3}$	0.0511	0.089*	0.0986*	0.0753*	0.0606	0.0031
$75plus_{t-3,t}$	0.31	0.26	0.3	0.33	0.33	0.27
$90plus_{t-3,t}$	0.18	0.19	0.18	0.08	0.11	0.03
	Divisional	Divisional/Type	Divisional/Subtype	Divisional	Divisional/Type	Divisional/Subtype
$\rho_{t,t-1}$	0.3433***	0.2729***	0.2287***	0.3545***	0.2597***	0.285***
$75plus_{t-1,t}$	0.45	0.41	0.33	0.43	0.4	0.43
$90plus_{t-1,t}$	0.3	0.23	0.26	0.3	0.26	0.33
$\rho_{t,t-2}$	0.1419***	0.092**	0.1316***	0.1851***	0.1015**	0.1216***
$75plus_{t-2,t}$	0.34	0.32	0.27	0.36	0.3	0.29
$90plus_{t-2,t}$	0.17	0.17	0.14	0.15	0.15	0.15
$\rho_{t,t-3}$	0.0232	0.0268	0.0947*	0.0532	0.0262	0.0144
$75plus_{t-3,t}$	0.32	0.31	0.27	0.29	0.28	0.24
$90plus_{t-3,t}$	0.2	0.17	0.1	0.08	0.11	0.07
	State	State/Type	State/Subtype	State	State/Type	State/Subtype
$\rho_{t,t-1}$	0.3095***	0.1592***	0.1673***	0.3295***	0.2597***	0.2516***
$75plus_{t-1,t}$	0.46	0.34	0.33	0.41	0.44	0.38
$90plus_{t-1,t}$	0.32	0.27	0.28	0.29	0.32	0.33
$\rho_{t,t-2}$	0.102**	0.0773*	0.0502	0.1463***	0.1297***	0.0402
$75plus_{t-2,t}$	0.3	0.32	0.28	0.35	0.36	0.28
$90plus_{t-2,t}$	0.21	0.16	0.14	0.15	0.25	0.18
$\rho_{t,t-3}$	−0.034	−0.0561	−0.0592	0.0592	0.0356	−0.0353
$75plus_{t-3,t}$	0.27	0.27	0.23	0.31	0.3	0.24
$90plus_{t-3,t}$	0.23	0.18	0.11	0.19	0.16	0.08
	CBSA	CBSA/Type	CBSA/Subtype	CBSA	CBSA/Type	CBSA/Subtype
$\rho_{t,t-1}$	0.364***			0.2904***		
$75plus_{t-1,t}$	0.5			0.39		
$90plus_{t-1,t}$	0.29			0.26		
$\rho_{t,t-2}$	0.1176***			0.1008**		
$75plus_{t-2,t}$	0.35			0.31		
$90plus_{t-2,t}$	0.19			0.2		
$\rho_{t,t-3}$	−0.0466			0.0248		
$75plus_{t-3,t}$	0.27			0.28		
$90plus_{t-3,t}$	0.18			0.17		

Table 11: Regression Results, CT Measures, Public Portfolios

Dependent variable: Quarterly CT measure by manager, for various aggregation levels of benchmark. This table presents results from panel regressions, by time and manager, for public portfolios. The independent variables are geographic portfolio specialization, property-type portfolio specialization, portfolio size, log of portfolio size and fractional turnover of the portfolio over time. All regressions contain year fixed-effects and standard errors clustered by manager.

	National		National/Type		National/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.002103	0.58	0.001850	0.46	0.000385	0.09
geo.spec	0.000911	0.94	−0.001527	−1.37	−0.000883	−0.77
type.spec	−0.000944	−1.04	0.002208	1.83°	0.001628	1.28
size	0.000000	2.27*	0.000000	2.47*	0.000000	2.63**
log(size)	−0.000415	−1.84°	−0.000842	−3.4***	−0.000742	−2.82**
turnover	−0.001904	−2.7**	−0.002394	−2.61**	−0.002351	−2.53*
$\overline{R^2}$	0.551		0.451		0.408	
F	352.665		235.761		195.519	
	Regional		Regional/Type		Regional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.002924	0.77	0.003280	0.79	0.003394	0.83
geo.spec	0.000772	0.74	−0.001527	−1.27	−0.000907	−0.72
type.spec	−0.000842	−0.92	0.001839	1.54	0.000867	0.67
size	0.000000	2.39*	0.000000	2.79**	0.000000	3.45***
log(size)	−0.000467	−2*	−0.000891	−3.51***	−0.000873	−3.67***
turnover	−0.001625	−2.29*	−0.002317	−2.34*	−0.002565	−2.43*
$\overline{R^2}$	0.508		0.402		0.316	
F	296.849		193.647		128.379	
	Divisional		Divisional/Type		Divisional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.004676	1.16	0.005941	1.43	0.007017	1.56
geo.spec	−0.000155	−0.15	−0.002180	−1.85°	−0.002082	−1.56
type.spec	−0.000967	−0.96	0.001210	0.98	0.001486	1.07
size	0.000000	2.41*	0.000000	2.92**	0.000000	3.49***
log(size)	−0.000603	−2.37*	−0.000999	−4***	−0.001139	−4.27***
turnover	−0.001763	−2.56*	−0.002128	−2.3*	−0.002270	−2.26*
$\overline{R^2}$	0.48		0.361		0.283	
F	265.361		162.881		108.085	
	State		State/Type		State/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.001584	0.35	0.007859	1.49	0.001585	0.26
geo.spec	0.000022	0.02	−0.002112	−1.47	−0.000221	−0.13
type.spec	−0.001238	−1.17	0.000751	0.54	0.000831	0.49
size	0.000000	2.29*	0.000000	2.57*	0.000000	1.7°
log(size)	−0.000547	−2.04*	−0.001057	−3.52***	−0.000732	−2.09*
turnover	−0.001875	−2.84**	−0.001855	−2.32*	−0.003275	−2.34*
$\overline{R^2}$	0.403		0.275		0.227	
F	194.037		106.185		72.291	
	CBSA		CBSA/Type		CBSA/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.002521	−0.57	0.006830	1.09	0.003335	0.45
geo.spec	0.000225	0.18	−0.003068	−1.85°	−0.001679	−1.01
type.spec	−0.001155	−1.01	−0.000315	−0.21	−0.000358	−0.21
size	0.000000	2.19*	0.000000	1.98*	0.000000	1.5
log(size)	−0.000488	−1.96*	−0.000934	−2.98**	−0.000734	−1.89°
turnover	−0.001893	−2.87**	−0.002877	−2.91**	−0.002267	−1.8°
$\overline{R^2}$	0.333		0.236		0.231	
F	141.542		78.115		60.72	

Table 12: Regression Results, CT Measures, Private Portfolios

Dependent variable: Quarterly CT measure by manager, for various aggregation levels of benchmark. This table presents results from panel regressions, by time and manager, for private portfolios. The independent variables are geographic portfolio specialization, property-type portfolio specialization, portfolio size, log of portfolio size and fractional turnover of the portfolio over time. All regressions contain year fixed-effects and standard errors clustered by manager.

	National		National/Type		National/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.010382	−1.91°	−0.008967	−1.65°	−0.010863	−2.04*
geo.spec	0.002977	2.26*	0.003671	2.39*	0.003413	2.21*
type.spec	0.000042	0.04	−0.001273	−1.05	−0.000880	−0.71
size	0.000000	0.63	0.000000	0.28	0.000000	−0.35
log(size)	0.000491	1.67°	0.000494	1.63	0.000602	2.1*
turnover	−0.001511	−5.73***	−0.001597	−5.45***	−0.001414	−4.71***
$\overline{R^2}$	0.524		0.496		0.489	
F	144.535		129.396		124.922	
	Regional		Regional/Type		Regional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.009521	−1.98*	−0.006815	−1.2	−0.008535	−1.54
geo.spec	0.002771	1.97*	0.003724	2.08*	0.003112	1.76°
type.spec	0.000038	0.03	−0.001405	−1.19	−0.001200	−0.92
size	0.000000	0.45	0.000000	0.76	0.000000	0.03
log(size)	0.000465	1.71°	0.000283	0.87	0.000400	1.24
turnover	−0.001335	−5.45***	−0.001423	−5.02***	−0.001256	−4.21***
$\overline{R^2}$	0.498		0.444		0.427	
F	130.321		104.894		97.388	
	Divisional		Divisional/Type		Divisional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.006082	−0.91	−0.007968	−1.27	−0.004864	−0.74
geo.spec	0.002837	1.63	0.004117	2.07*	0.002930	1.35
type.spec	0.000067	0.06	−0.000688	−0.55	−0.000546	−0.39
size	0.000000	0.2	0.000000	0.55	0.000000	0.25
log(size)	0.000470	1.37	0.000329	0.94	0.000310	0.82
turnover	−0.001121	−4.44***	−0.001143	−3.67***	−0.000910	−2.66**
$\overline{R^2}$	0.489		0.423		0.403	
F	125.449		96.573		87.509	
	State		State/Type		State/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.004266	−0.65	−0.003003	−0.45	0.006066	0.73
geo.spec	0.001942	1.03	0.003117	1.51	0.002234	0.85
type.spec	−0.000447	−0.35	−0.001405	−1.06	−0.000213	−0.13
size	0.000000	0.64	0.000000	0.81	0.000000	0.92
log(size)	0.000301	0.78	0.000135	0.36	−0.000028	−0.06
turnover	−0.001279	−4.35***	−0.001399	−3.87***	−0.000953	−2.61**
$\overline{R^2}$	0.449		0.378		0.342	
F	106.796		79.337		66.17	
	CBSA		CBSA/Type		CBSA/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	−0.007182	−0.97	−0.008609	−1.09	0.001147	0.11
geo.spec	0.002575	1.2	0.002214	0.9	−0.000308	−0.09
type.spec	−0.000526	−0.37	0.000567	0.38	0.000268	0.14
size	0.000000	0.08	0.000000	−0.02	0.000000	−0.04
log(size)	0.000537	1.27	0.000490	1.03	0.000226	0.37
turnover	−0.001158	−3.75***	−0.001244	−2.89**	−0.000852	−1.73°
$\overline{R^2}$	0.385		0.319		0.287	
F	81.072		59.52		47.849	

Table 13: Regression Results, CS Measures, Public Portfolios

Dependent variable: Quarterly CS measure by manager, for various aggregation levels of benchmark. This table presents results from panel regressions, by time and manager, for public portfolios. The independent variables are geographic portfolio specialization, property-type portfolio specialization, portfolio size, log of portfolio size and fractional turnover of the portfolio over time. All regressions contain year fixed-effects and standard errors clustered by manager.

	National		National/Type		National/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.013835	2.51*	0.009859	2.05*	0.009668	1.95°
geo.spec	−0.002502	−1.65°	−0.001805	−1.34	−0.002409	−1.69°
type.spec	−0.001880	−1.24	−0.000852	−0.65	−0.000778	−0.59
size	0.000000	0.53	0.000000	0.62	0.000000	0.12
log(size)	−0.000839	−2.41*	−0.000688	−2.24*	−0.000659	−2.09*
turnover	0.001691	2.25*	0.001266	1.96°	0.001410	2.44*
$\overline{R^2}$	0.018		0.017		0.029	
F	6.036		5.67		8.885	
	Regional		Regional/Type		Regional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.014423	2.49*	0.009423	2.06*	0.008808	1.85°
geo.spec	−0.002255	−1.46	−0.001617	−1.25	−0.002323	−1.49
type.spec	−0.001681	−1.34	−0.001138	−1.22	−0.000757	−0.73
size	0.000000	0.73	0.000000	1.29	0.000000	0.84
log(size)	−0.000868	−2.3*	−0.000609	−2.12*	−0.000517	−1.81°
turnover	0.001784	2.29*	0.001339	2.27*	0.001295	2.54*
$\overline{R^2}$	0.013		0.011		0.016	
F	4.412		4.008		5.127	
	Divisional		Divisional/Type		Divisional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.013603	2.51*	0.009240	2.58*	0.009278	1.99*
geo.spec	−0.001965	−1.29	−0.001450	−1.17	−0.002566	−1.63
type.spec	−0.001528	−1.23	−0.001542	−1.86°	−0.001515	−1.56
size	0.000000	0.74	0.000000	1.6	0.000000	1.03
log(size)	−0.000810	−2.31*	−0.000520	−2.35*	−0.000444	−1.49
turnover	0.001836	2.57*	0.001409	2.97**	0.001703	3.18**
$\overline{R^2}$	0.011		0.011		0.014	
F	3.956		3.98		4.613	
	State		State/Type		State/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.010242	1.91°	0.004876	1.67°	0.001979	0.62
geo.spec	−0.002710	−1.9°	−0.001392	−1.32	−0.001394	−1.06
type.spec	−0.001025	−0.86	−0.000552	−0.79	−0.000120	−0.16
size	0.000000	0.43	0.000000	0.88	0.000000	−0.59
log(size)	−0.000631	−1.82°	−0.000300	−1.64	−0.000083	−0.41
turnover	0.001824	2.48*	0.000801	1.71°	0.001299	3.41***
$\overline{R^2}$	0.011		0.004		0.008	
F	3.871		1.931		2.759	
	CBSA		CBSA/Type		CBSA/Subtype	
	Coefficient	t-statistic				
(Intercept)	0.006983	1.65°				
geo.spec	−0.001670	−1.48				
type.spec	−0.001032	−0.98				
size	0.000000	0.18				
log(size)	−0.000418	−1.55				
turnover	0.001509	2.44*				
$\overline{R^2}$	0.006					
F	2.667					

Table 14: Regression Results, CS Measures, Private Portfolios

Dependent variable: Quarterly CS measure by manager, for various aggregation levels of benchmark. This table presents results from panel regressions, by time and manager, for private portfolios. The independent variables are geographic portfolio specialization, property-type portfolio specialization, portfolio size, log of portfolio size and fractional turnover of the portfolio over time. All regressions contain year fixed-effects and standard errors clustered by manager.

	National		National/Type		National/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.004572	0.63	0.006979	0.84	0.014144	1.46
geo.spec	−0.002173	−0.89	−0.002037	−0.69	−0.002586	−0.78
type.spec	0.002283	1.4	0.002197	1.79°	0.001331	1.06
size	0.000000	1.99*	0.000000	1.58	0.000000	1.84°
log(size)	−0.000640	−1.4	−0.000459	−0.86	−0.000895	−1.45
turnover	−0.000117	−0.45	−0.000114	−0.45	−0.000129	−0.49
$\overline{R^2}$	0.025		0.012		0.012	
F	3.962		2.414		2.434	
	Regional		Regional/Type		Regional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.006912	1.11	−0.002185	−0.33	−0.000283	−0.03
geo.spec	−0.002049	−0.98	−0.001012	−0.43	−0.000146	−0.05
type.spec	0.002025	1.22	0.002138	1.94°	0.002085	1.91°
size	0.000000	1.71°	0.000000	0.69	0.000000	0.92
log(size)	−0.000416	−1.12	−0.000023	−0.06	−0.000123	−0.24
turnover	−0.000244	−1.04	−0.000239	−1.2	−0.000174	−0.76
$\overline{R^2}$	0.016		0.003		0.004	
F	2.842		1.396		1.42	
	Divisional		Divisional/Type		Divisional/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.007515	1.34	−0.000397	−0.08	−0.000856	−0.12
geo.spec	−0.002371	−1.25	−0.001475	−0.72	−0.000330	−0.1
type.spec	0.001518	0.98	0.001205	1.37	0.001295	1.33
size	0.000000	1.65°	0.000000	0.57	0.000000	0.67
log(size)	−0.000476	−1.41	−0.000114	−0.36	−0.000096	−0.21
turnover	−0.000161	−0.71	−0.000123	−0.65	0.000059	0.27
$\overline{R^2}$	0.017		0.008		0.012	
F	2.989		1.938		2.437	
	State		State/Type		State/Subtype	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
(Intercept)	0.003366	0.69	−0.002726	−0.61	−0.003621	−0.49
geo.spec	−0.001418	−0.74	0.000224	0.13	0.001634	0.5
type.spec	0.000974	0.67	0.000669	0.83	0.001009	1.17
size	0.000000	1.78°	0.000000	0.36	0.000000	0.48
log(size)	−0.000427	−1.35	−0.000100	−0.37	−0.000048	−0.1
turnover	−0.000232	−1.07	0.000034	0.21	0.000311	1.52
$\overline{R^2}$	0.013		0.006		0.012	
F	2.542		1.672		2.358	
	CBSA		CBSA/Type		CBSA/Subtype	
	Coefficient	t-statistic				
(Intercept)	0.005193	1.31				
geo.spec	−0.001706	−1.21				
type.spec	0.000321	0.26				
size	0.000000	1.92°				
log(size)	−0.000441	−1.76°				
turnover	−0.000240	−1.28				
$\overline{R^2}$	0.008					
F	1.944					