Asset Location, Timing Ability, and the Cross-Section of Commercial Real Estate Returns

by

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Current Draft: March 2017

Abstract:

This study examines the sensitivity of equity REIT returns to time-varying MSA allocations of REIT property portfolios. Using a large sample of individual commercial property holdings, we find significant cross-sectional and time variation in REIT geographic exposures and the ability of these exposures to explain the cross-section of REIT returns. Importantly, the pattern of MSA exposure effects changes quickly as local market information is incorporated into property values both across MSAs and over time. We further find evidence consistent with REIT managers being able, on average, to both identify MSAs that will outperform in the following year and overcome the costs and delays associated with increasing allocations to these MSAs. This ability to time allocation decisions is most prevalent in non-Gateway markets and varies significantly across MSAs and over time. Furthermore, financially flexible firms with a larger platform and experience owning and operating properties in multiple markets are better positioned to quickly act on investment opportunities they identify in major MSAs. In contrast, the ability to time market exit is more highly correlated with a firm's perceived growth options and investment opportunities.

We thank Brad Case, Shawn Howton, Shelly Howton, Calvin Schnure, Xiaolu Wang, John Worth, Seminar participants at Iowa State University, and participants at UNC-Chapel Hill's 2016 Real Estate Research Conference for helpful comments.

Keywords: Location, Market Timing, Real Estate Returns

JEL Codes: D82, G11, R3

Introduction

One of the best known adages in real estate is that the three most important determinants of property value are location, location, and location. Despite the importance of location, the existing commercial real estate (CRE) literature does not consider cross-sectional and time-series variation in the MSA locations of portfolio properties when explaining returns. Given observed differences in property portfolio concentrations and variation in realized return performance across geographic locations, an important question remains: to what extent do time-varying exposures to individual metropolitan statistical areas (MSAs) affect the cross-section of CRE returns?[1]

The variation in realized return performance across MSAs and their submarkets results largely from unexpected changes in the demand and supply of leasable space and, therefore, in rental rates. Real estate investors, including REIT managers, must form expectations of the prospects for urban growth, for changes in transportation and communication networks, for changes in land-use controls, and for trends in the mix and character of employment activities in their MSA investment decisions. Thus, the choice of asset location in CRE investments requires significant due diligence rooted in a deep understanding of a city's economic base, the linkages and infrastructure available within the urban matrix, the competitiveness of local capital markets, the burdens of the regulatory environment, and other sources of competitive advantage embedded within the geographic landscape. To the extent market participants anticipate these differential factors on rent, their effect should be quickly capitalized into property values in competitive CRE markets. However, market frictions in relatively illiquid and highly segmented private markets impede the timely capitalization of changing expectations into property values. As a result, the effects of both expected and unanticipated shocks to local market conditions on returns may be discernable over longer horizons, giving portfolio managers the opportunity to adjust property allocations to take advantage of changing market conditions.

While there is clear tension on the potential return effects of MSA allocations, this line of research has received limited attention in the literature. Prior empirical work has focused on explaining return dynamics across geographic markets by identifying

[1] In June of 2003, the U. S. Office of Management and Budget adopted new standards for Metropolitan Areas (OBM-https://www.whitehouse.gov/omb/inforeg_statpolicy#ms). A metropolitan statistical area (MSA) has at least one urbanized area with a population of at least 50,000, based on the 2000 Census. As of June 6, 2003, the OMB has defined a total of 362 Metropolitan Statistical Areas containing approximately 83% of the US population.

commonalities in MSA characteristics. For example, Hartzell et al. (1986, 1987) and Mueller and Ziering (1992) suggest significant differences in the economic base of MSAs produce different risk exposures across geographic locations. Others, including Riddiough et al. (2005) and Nichols et al. (2013), have identified variation in supply constraints across geographic markets as a potential driver of return differences among property portfolio managers. Performance differences across MSAs have also been attributed to cross-sectional variation in a city's exposure to macro-economic shocks (Cotter, Gabriel, and Roll, 2014). Taken together, the related literature suggests MSA allocations are a potentially important factor in CRE return performance. However, prior work in CRE, including Riddiough et al. (2005), cite a lack of reliable data on the property holdings of CRE investors as a primary reason for the omission of geographic variables from their analyses.

Using granular property location data, a recent stream of research has emerged examining how differences in geographic concentrations of public and private commercial real estate portfolios impacts relative return performance.[2] We extend this literature by analyzing the impact of *individual* MSA exposures on returns *within* the public CRE market. In so doing, we provide direct evidence of the relative importance of time-varying geographic exposures in explaining the cross-section of REIT returns. We also document cross-sectional differences in the ability of equity REIT managers to effectively time portfolio acquisitions and dispositions in anticipation of expected performance variation across MSAs. Our market timing analysis complements and extends recent work by Hochberg and Muhlhofer (2016) that also examines the market timing ability of CRE portfolio managers.

Equity REITs provide an ideal setting to analyze and test geographic exposures and manager timing effects in CRE returns for several reasons. First, equity REITs typically acquire and dispose of CRE in a "parallel" private market. This parallel market setting allows us to align cross-sectional and time-varying differences in MSA performance in the underlying property market with geographic allocation decisions of property portfolio managers. Second, recent research suggests certain institutional features of public REIT markets may inhibit a manager's ability to vary geographic allocations in accordance with real estate cycles. For example, Muhlhofer (2013) focuses on the so-called "dealer rule" as a trading constraint that may prevent REITs from consistently generating appreciation

[2] For example, recent work by Ling, Naranjo, and Scheick (2016), highlight the importance of controlling for differences in geographic allocation decisions in comparisons of commercial real estate portfolio performance across public and private markets.

returns from portfolio disposition decisions. REIT managers also face implicit mandates from investors to concentrate allocations within a specific property type (or subtypes) and geographic markets. If managers are constrained in their ability to adjust portfolio exposures, performance differences across geographic markets have the potential to be persistent. In the presence of such frictions, individual MSA exposures should become an increasingly important determinant of portfolio returns.

Using SNL's Real Estate Database, we directly measure a firm's exposure to an individual MSA in a particular year from 1996-2013. As expected, REITs tend to have greater allocations to larger "gateway" markets and smaller average exposures to secondary markets. We also observe significant cross-sectional and time series variation in firm-level exposures to major MSAs.

To investigate the extent to which REIT returns are related to time-varying MSA allocations, we estimate a series of panel and cross-sectional (Fama-MacBeth, 1973) regressions of annual REIT returns on standard firm-level control variables augmented by firm-level MSA allocations. Despite the widely-held belief that location is a prime determinant of CRE returns, we find only a few MSA allocations have significant coefficient estimates in our panel regressions.

The panel regressions produce an estimate of the average sensitivity of REIT returns to their exposure to each MSA over an 18-year period. However, this average effect masks potentially substantial time series variation in MSA exposures. In contrast, our annual cross-sectional regressions allow coefficient estimates, including MSA exposures, to vary over time. Controlling for firm-level allocations to CRE in 25 major MSAs increases the average adjusted R-square from our annual cross sectional regressions by 12 percentage points, an economically and statistically significant increase in explanatory power. Importantly, a much larger number of MSA allocations are statistically significant (on average) when our estimated exposures are allowed to vary over time. However, the MSA exposures that are significant in a given year vary substantially over the 18-year sample. In addition, many of the MSAs that do not provide significant explanatory power, on average, do have positive and significant coefficients in some years and negative and significant coefficients in other years.

This substantial time-series variation in estimated MSA coefficients is consistent with generally well-functioning capital markets. If expectations about the prospects for rent growth in a MSA change, CRE prices adjust to embed these changing expectations. Thus, a positive unexpected shock to rent growth expectations in a MSA increases prices, and therefore returns, to the current owners of CRE in that MSA. However, once the positive expectations shock is fully embedded in property prices, investors are unable to earn excess returns by investing in properties in that MSA. That is, the effects of expectations shocks on MSA prices and returns are not persistent in competitive CRE markets. Moreover, positive expectations shocks are likely to be averaged away by offsetting negative shocks as the time horizon over which MSA exposures are estimated increases. Overall, our results suggest MSA allocations matter in the return generating process; however, the return enhancing (or destroying) abilities of particular MSA allocations change rapidly.

After establishing the cross-sectional and time varying nature of geographic exposures, we also investigate the ability of REIT managers to effectively time portfolio acquisitions and dispositions in anticipation of expected performance differences across MSAs. Given the parallel market framework, we combine firm-level portfolio allocations with MSA-level return performance using data for the private CRE market provided by the National Council of Real Estate Investment Fiduciaries (NCREIF). With these data, we develop a parametric test of market timing ability in the spirit of Merton and Henriksson (1981). In particular, we examine whether the ability of REIT managers to time increased allocations to top performing private CRE markets and decrease allocations to poorly performing markets impacts the cross-section of REIT returns.

The successful timing of MSA allocations requires managers to predict changes in the prospects of a MSA and complete the acquisition or disposition of properties before these changes are fully reflected in the expectations of the marginal investor in that MSA. We provide evidence consistent with REIT managers being able to both identify MSAs that will outperform in the following year and overcome the costs and delays associated with increasing allocations to these MSAs. However, we find the ability to time allocation decisions is concentrated in non-Gateway markets and varies significantly across MSAs.

We also document that the ability to time entry into high performing markets is concentrated in well diversified REITs and those with relatively low levels of financial constraint. That is, financially flexible firms with a larger platform and experience owning and operating properties in multiple markets are better positioned to quickly act on investment opportunities they identify in major MSAs. Furthermore, the ability to time market exit is more highly correlated with a firm's perceived investment opportunities. That is, managers are more willing to decrease exposure to a market ahead of poor performance as long as viable investment opportunities are perceived to be available in other markets.

Taken together, our market timing results extend recent work on the relative importance of asset allocation decisions in CRE performance evaluation (e.g., Ling, Naranjo, and Scheick, 2016; Hochberg and Muhlhofer, 2016). While prior work finds geographic allocation decisions explain only a small portion of performance differences *across* public and private CRE markets (e.g., Ling, Naranjo, and Scheick, 2016), we provide evidence of geographic market timing ability *within* the cross-section of listed REITs. Our market timing results are also robust to a number of alternative specifications and variable definitions.

Overall, this paper contributes to the broader literature on the determinants of REIT returns by documenting the extent to which individual MSA exposures impact portfolio returns in the public CRE market. To our knowledge, we are the first to quantify the extent to which individual MSA allocations affect the cross-section of CRE returns.[3] We also contribute to the market timing literature by documenting the influence on REIT performance of time-varying portfolio allocations towards (away from) geographic markets that subsequently outperform (underperform). In this regard, we also provide new evidence of significant cross-sectional differences in the characteristics of REITs that are able to take advantage of time-varying geographic market conditions, as well as the MSAs in which REITs have exhibited positive timing ability.

The remainder of the paper proceeds as follows. *Data and Variable Construction* describes our data and discusses our construction of firm-level, time-varying MSA allocations. *MSA Concentrations and REIT Returns* presents the results from estimating our panel regressions and Fama-MacBeth cross-sectional regressions of the effects of MSA allocations on returns. *Time Varying MSA Exposures and Market Timing Ability* contains our analysis of the ability of REIT managers to time entry and exit into high performing and low performing MSAs. We provide concluding remarks in the final section.

Data and Variable Construction

To examine the importance of time-varying geographic concentrations, we collect the following data from SNL's Real Estate Database on an annual basis for each property held by a listed equity REIT during the period 1996 to 2013: property owner (institution name), property type, geographic (MSA) location, acquisition date, sale date, book value, initial cost,

[3] Earlier work by Gyourko and Nelling (1996), Capozza and Seguin (1998) Ambrose et al. (2000), Campbell (2003) and Hartzell et al. (2014) focus on the relation between the cross-section of returns and the overall geographic diversification of the property portfolio, rather than the importance of individual MSA exposures in determining firm-level returns.

and historic cost. Our analysis begins in 1996 (end of 1995) because this is the first period SNL provides historic cost and book value information at the property level. We focus our analysis on properties held by core REITs; that is, REITs classified by CRSP-Ziman as focusing on apartment, office, industrial, or retail properties.

The 25 major U.S. MSAs were chosen based on the following criteria: (1) the MSA was ranked in the top 30 MSAs based on population in at least two of the last three United States Census reports (i.e., 1990, 2000, 2010) and (2) NCREIF produced total return indices for each of the four core property types over our full sample period. Our selection criteria leaves us with the following 25 MSAs: Atlanta, Boston, Chicago, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C.

Our property-level dataset includes 153,777 property-year observations for 104 unique REITs over our 1996-2013 sample. At the beginning of 1996, core REITs held 4,806 properties with a reported book value of approximately $11 billion in the 25 geographic markets we track. By the beginning of 2013, core REITs held 7,887 properties with a reported book value of $168 billion in these markets. Figure 1 presents the concentrations of core properties located in our 25 MSAs. On average, equity REITs held approximately 60 percent of their portfolio in these MSAs over the sample period, with nearly half of these properties located in gateway markets (i.e., Boston, Chicago, Los Angeles, New York, San Francisco, and Washington, D.C.). We also observe a substantial increase in equity REIT exposure to the 25 major markets over our sample period, ranging from approximately 40 percent of their portfolios in 1996 to over 70 percent in 2013.

We construct yearly time-varying measures of geographic concentrations in the 25 MSAs at the firm level to better understand the impact of geographic exposures on the cross-section of REIT returns. We first sort each core REIT's properties at the beginning of each year into the 25 MSAs. We then compute the percentage of firm f's portfolio held in each MSA at the beginning of year T as:

$$GEO_{f,m,T} = \frac{\sum_{i=1}^{N_{m,T}}(ADJCOST_{i,m,T})}{\sum_{m=1}^{N_T}\left(\sum_{i=1}^{N_{m,T}}(ADJCOST_{i,m,T})\right)} \ , \tag{1}$$

where $ADJCOST_{i,m,T}$ is the "adjusted cost" of property i in Metropolitan Statistical Area m at the beginning of year T. $ADJCOST$ is defined by SNL as the maximum of (1) the current book value, (2) the initial cost of the property, and (3) the historic cost of the property including capital expenditures and tax depreciation.[4] The total number of properties held by firm f in a particular MSA at the beginning of year T is denoted as $N_{m,T}$. The total number of MSAs in which the firm invested as of the beginning of year T is denoted as N_T.

Table 1 presents descriptive statistics for our firm-level concentration measures for each of the 25 MSAs. As expected, core REITs tend to apply greater portfolio weights to gateway markets such as New York, Los Angeles and Washington, D.C. and have smaller average exposures to secondary markets such as St. Louis, Sacramento, and San Antonio. However, the average allocation to Boston, generally considered one of the six gateway markets, is just 1.3 percent. We also observe significant cross-sectional variation in firm-level exposures to an MSA over our sample period. For example, firm-level concentrations in New York vary from 0 to 100 percent in the cross-section. Average concentrations also display significant time-series variation. For example, average concentrations in New York range from approximately 6 percent in 1996 to 12 percent in 2013.

To understand how these differences in geographic exposures impact the cross-section of REIT returns, it is important to first establish there are significant performance differences across MSAs. We utilize return data for the private CRE market from the National Council of Real Estate Investment Fiduciaries (NCREIF) to examine these differences. NCREIF's flagship index, the NCREIF Property Index (NPI), tracks property-level quarterly returns on a large pool of properties acquired in the private market for investment purposes only.[5] Table 2 provides descriptive statistics for annualized NCREIF NPI returns disaggregated by MSA at the core property type level. Mean returns and standard deviations are plotted in Figure 2. Gateway MSAs generally outperformed, on average, their counterparts, on a raw total return basis over our sample period. However, there is significant variation in average returns across the 25 markets we track. For example, average MSA returns for core properties range from 12.6 percent in San Diego to 2.2 percent in Miami. We also observe substantial time-series variation of returns within MSAs.

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[4] SNL's initial cost variable (SNL Key Field: 221778) is defined as the historic cost currently reported on the financial statements, which may be different than the cost reported at time of purchase. SNL's historic cost variable (SNL Key Field: 221782) is defined as the book value of the property before depreciation.

[5] Established in 1982, NCREIF is a not-for-profit institutional real estate industry association that collects, processes, validates, and disseminates information on the risk/return characteristics of commercial real estate assets owned by institutional (primarily pension and endowment fund) investors. The property composition of the NPI changes quarterly as data contributing NCREIF members buy and sell properties. However, all historical property-level data remain in the database and index.

Exposure to San Francisco core properties exhibits the most time-series variation in returns, ranging from a high of 27.8 percent in 1998 to a low of -24.3 percent in 2009. Taken together with our observations of firm-level concentrations in these MSAs, the cross-sectional and time series variation in MSA private market returns suggests portfolio managers have the opportunity to actively shift geographic allocations to time real estate cycles across geographic regions.

If REIT managers can effectively time geographic allocations, we would expect time-series variation in geographic exposures to explain a significant portion of the cross-section of REIT returns, controlling for other factors known to affect these returns. To test this hypothesis, we obtain annual firm-level data from the CRSP-ZIMAN database for all core equity REITs over the full sample period. We define $R_{i,t}$ as the firm's annual total return. We also collect annual data from SNL Real Estate on firm characteristics known to be important determinants of the cross-section of returns. We define *SIZE* as the natural log of the firm's aggregate market capitalization in billions of dollars, *M/B* as the market value of assets divided by the book value of assets, *MOMENTUM* as the firm's cumulative return over the prior year, *ILLIQ* as the natural logarithm of the stock's Amihud (2002) illiquidity measure, and *LEV* as the total book value of debt divided by the book value of total assets. These firm characteristics are measured at the end of the year prior to which returns are measured. Our full sample consists of 1,044 firm-year observations.

Table 3 reports summary statistics for our panel dataset. Annual returns averaged 12.9 percent with a standard deviation of 26.5 percent. The average equity market capitalization was $1.7 billion with a standard deviation of $2.45 billion. The average market-to-book ratio for our sample is 1.8. Firms exhibit positive return appreciation over the prior year, on average, although significant variation is observed. Total leverage averaged 42.1 percent over the sample period. There is, however, substantial variation in leverage across firms and over time.

MSA Concentrations and REIT Returns

This section investigates the extent to which the inclusion of time-varying MSA allocations, as additional firm characteristics, helps explain cross-sectional variation in equity REIT returns. To investigate how equity REIT returns are related to MSA allocations, we estimate both panel regressions and a series of Fama-MacBeth annual cross-sectional regressions.

Panel Regressions

We first estimate the following baseline panel regression:

$$RET_{i,t} = \alpha + \beta_1 SIZE_{i,t-1} + \beta_2 M/B_{i,t-1} + \beta_3 MOMENTUM_{i,t-1} + \beta_4 ILLIQ_{i,t-1} + \beta_5 LEV_{i,t-1} + \varepsilon_{i,t}\,, \quad (2)$$

where $RET_{i,t}$ is the firm's excess return in year t with respect to the yield on the one-month Treasury bill. Property type fixed effects are included in these REIT regressions.

Table 4, column (1) presents the coefficients and p-values from estimating equation (2) for all REITs designated by CRSP-Ziman as having an apartment, office, industrial, or retail property focus.[6] The estimated coefficient on *SIZE* over our 18 year sample is negative and highly significant. REITs with higher market-to-book ratios (more growth options) at the beginning of the year perform worse over the next 12 months. *MOMENTUM* is positively and significantly related to returns (p-value=0.049). The estimated coefficient on *ILLIQ* is negative and highly significant. Finally, increased leverage is associated with higher returns over the next 12 months. This standard panel regression explains 10 percent of the annual variation in core REIT returns.

We next augment our baseline specification by adding beginning-of-year allocations, based on the adjusted cost of each property, to the six gateway markets. These results are reported in column (2) of Table 4. The estimated coefficient on the gateway concentration variable (*CON_GATEWAY*) is positive and highly significant (p-value=0.017). The inclusion of the gateway exposure variable increases the adjusted R-square from 10 percent to 11 percent.

In column (3) of Table 4, we replace the gateway concentration variable with the proportion of the firm's portfolio concentrated in the 25 MSAs. The estimated coefficient on the broader concentration variable (*CON*) is positive, although smaller in magnitude than the gateway concentration variable and only marginally significant (p-value=0.081). The inclusion of the broader exposure variable also increases the adjusted R-square from 10 percent in our base case to 11 percent.

Finally, we add the beginning-of-year allocations of each REIT to each of the 25 MSAs. More specifically, we estimate the following augmented panel regression:

[6] CRSP-Ziman regularly reviews the property type focus of all REITs in their U.S. universe and changes the designated property type focus of each REIT when necessary.

$$RET_{i,t} = \alpha + \beta_1 SIZE_{i,t-1} + \beta_2 M/B_{i,t-1} + \beta_3 MOMEMTUM_{i,t-1} + \beta_4 ILLIQ_{i,t-1} + \beta_5 LEV_{i,t-1} + \sum_1^{25} Y_{m,i} MSA_{m,i,t-1} + \varepsilon_{i,t} , \tag{3}$$

where $MSA_{m,i,t-1}$ is firm *i*'s allocation to MSA *m* at the end of year t-1. Property type fixed effects are included. These results are reported in column (4) of Table 4. Allocations to New York, San Francisco, Orlando, and San Diego, are associated with increased returns on core properties over the next 12 months. In contrast, allocations to Houston and Sacramento reduced firm-level returns, on average, over our sample period. Allocations to the remaining 19 MSAs have no statistically significant effect on the typical core REIT's returns. Despite the widely-held belief that location is a prime determinant of CRE returns, controlling for cross-sectional variation in exposures to the major MSAs increases the explanatory power of the panel regression by less than one percentage point.

Fama-MacBeth Regressions

A potential limitation of the panel regressions is they constrain coefficient estimates to be constant over the 18 year sample period. To allow estimates to vary over time, we perform annual cross-sectional regressions similar to Fama-MacBeth (1973). In particular, we estimate the following Fama-MacBeth regression model:

$$RET_{i,t} = c_0 + \sum_{m=1}^{M} c_{i,m} Z_{m,i,t-1} + \varepsilon_{i,t}, \tag{4}$$

where $Z_{m,i,t-1}$ is one of *M* firm characteristics including *SIZE, M/B*, *MOMENTUM*, *ILLIQ*, *LEV*, and our set of geographic allocation variables.

Table 4, column (5) presents the time series averages and associated p-values of the cross-sectional regression coefficients from jointly estimating the baseline model for all REITs having an apartment, office, industrial, or retail property focus. Property type fixed effects are included in the specification. Similar to our panel regressions, the average cross-sectional coefficient on *SIZE* is negative and highly significant. *MOMENTUM* is positive and significantly related to returns (average p-value=0.007). The average cross sectional coefficient on *ILLIQ* is negative and highly significant. Finally, in contrast to our panel regression results, market-to-book ratios and leverage do not significantly affect returns over the next 12 months. On average, this baseline cross-sectional model explains 23 percent of the annual variation in core REIT returns, substantially more explanatory power than our panel regressions.

We next augment our baseline specification by adding the beginning-of-year allocations to the six gateway markets. The average cross sectional coefficient on this allocation is positive and significant (p-value=0.047). The inclusion of the gateway allocation variable increases the adjusted R-square from 23 to just 24 percent. The results reported in the next column of Table 4 include the coefficient estimate on the proportion of the firm's portfolio concentrated in the 25 MSAs. The broader concentration measure (*CON*) is insignificant, and the adjusted R-square remains 24 percent.

The final column in Table 4 presents results that include allocations to each of the 25 MSAs. As with our panel regressions, the average coefficient on exposure to New York and San Francisco is positive and significant. However, unlike our panel results, the estimated coefficient on exposure to LA and Chicago are negative and marginally significant. On average, allocations to New York, San Francisco, St. Louis, and Kansas City are associated with increased returns on core properties over the next 12 months. In contrast, allocations to LA., Chicago, Philadelphia, Houston, Tampa, and Indianapolis reduced firm-level returns, on average, over our sample period. On average, allocations to the remaining 15 MSAs have no statistically significant effect on the typical core REIT's returns.

Controlling for firm-level allocations to core properties in these 25 major MSAs increases the average adjusted R-square to 35 percent from 23 percent, a much larger increase in explanatory power than in our panel regressions. An F-test reveals the difference in R^2 is significant at the 5 percent level. Although not separately tabulated, the MSAs that come in significant in a given year vary substantially over the 18 year sample. Moreover, many of the MSAs that provide no significant explanatory power, on average, do have positive and significant coefficients in some years and negative and significant coefficients in other years. However, there is no clear pattern in the MSA effects. Overall, these core results suggest that MSA location matters; however, the return enhancing (or destroying) abilities of particular MSAs appear to change rapidly. In our market timing analysis, we further examine whether REIT managers are able to both predict these changes in MSA location values and to act on these predictions in a timely manner.

Further Robustness Using Geographic Regions, Economic Base, and Industry Clusters

Prior approaches to measuring geographic risk exposure have relied on broader classifications of asset location based on geographic region, economic base and industry clusters (e.g., Mueller and Ziering, 1992; Mueller, 1993; Miles and McCue, 1984; Hartzell, 1986, 1987). One reason for this has been the lack of granularity in property portfolio data. Using broader asset allocation categories, we estimate three additional regressions to demonstrate the added value of including *individual* MSA exposures to explain the cross-section of REIT returns.

We begin by sorting the 25 MSAs into one of the following eight geographic regions (Northeast, Mideast, Southeast, East North Central, West North Central, Southwest, Mountain and Pacific), as classified by SNL, and construct firm-level geographic concentration measures pertaining to each region as of the beginning of each year.[7] We then estimate a Fama-MacBeth regression model similar to equation (4) that includes the eight regional concentration variables in place of our individual MSAs. In untabluated results, we find that controlling for firm-level allocations to the eight geographic regions increases the average adjusted R-square from 23 percent to 28 percent. Although this difference is statistically significant at the 5 percent level, it is smaller in magnitude than what we previously documented with individual MSA exposures. In contrast to our MSA results, none of the average coefficients on the eight geographic regions are statistically significant. These results are consistent with regional measures of geography masking the cross-sectional variation in individual MSA exposures within regions.

We repeat the analysis using two alternate geographic classifications. Following Hartzell et al. (1987) we sort the 25 MSAs into one of the following eight economic activity regions (New England; Mid-Atlantic Corridor; Old South; Industrial Midwest; Farm Belt; Mineral Extraction Area; Southern California; and Northern California).[8] As an alternative to economic regions, we also sort MSAs into seven industry clusters (Professional and Business; Government; Information and Finance; Leisure and Hospitality; Education and Health Services; Natural Resources, Construction, and Manufacturing; and Trade, Transportation, and Utilities), similar to Mueller and Ziering (1992) and Mueller (1993).[9] In

[7] MSA constituents for each geographic region are as follows: Northeast (Boston, New York, Philadelphia), Mideast (Washington D.C.), Southeast (Atlanta, Miami, Orlando, Tampa), East North Central (Chicago, Detroit, Indianapolis), West North Central (Kansas City, Minneapolis, St. Louis), Southwest (Dallas, Houston, San Antonio), Mountain (Denver, Phoenix), and Pacific (Los Angeles, Portland, Sacramento, San Diego, San Francisco, Seattle).

[8] MSA constituents for each economic region are as follows: New England (Boston), Mid-Atlantic Corridor (New York, Philadelphia, Washington, D.C.), Old South (Miami, Atlanta, Tampa, Orlando), Industrial Midwest (Chicago, Detroit, Indianapolis), Farm Belt (Kansas City, Minneapolis, St. Louis), Mineral Extraction Area (Dallas, Houston, San Antonio, Denver), Southern California (Los Angeles, Phoenix, San Diego), and Northern California (San Francisco, Sacramento, Seattle, Portland).

[9] MSA constituents for each industry cluster are as follows: Professional and Business (San Francisco, San Diego), Government (Washington, D.C., Sacramento), Information and Finance(New York, San Antonio), Leisure and

each case, we again construct firm-level geographic concentration measures pertaining to each geographic category as of the beginning of each year and estimate annual Fama-MacBeth regressions. Controlling for firm-level allocations to these sectors produces average adjusted R-squares of 27 and 26 percent, respectively. Comparing these R-square estimates to that of our baseline specification reveals statistically significant differences at the 5 and 10 percent level, respectively. However, only one coefficient estimate across the two specifications is statistically significant. Overall, these additional tests suggest broader geographic and industrial concentrations are insufficient substitutes for more granular, *individual* MSA risk exposures.

Time Varying MSA Exposures and Market Timing Ability

The Fama-MacBeth cross-sectional regression results reported in Table 4 suggest a limited role for MSA allocations in explaining the cross-section of REIT returns. However, average coefficient estimates and p-values mask substantial variation in estimated MSA exposures from year to year. To demonstrate this point, we first plot estimated MSA betas from our annual cross-sectional regressions across time for a single MSA (New York) in Panel A of Figure 3. We observe significant variation and minimal persistence in the annual betas for NY. Although the average exposure effect to the NY market is positive, periods of positive beta exposure are often followed by negative beta exposure and vice versa. These reversals may be indicative of well-functioning capital and property markets. That is, if returns in a particular MSA increase, perhaps due to a favorable exogenous shock to rental rates, investment capital will flow to these MSAs, thereby driving up property prices and reducing subsequent returns (all else equal).

In Panel B of Figure 3, we plot the number of positive and negative allocation betas for each MSA, without concern for statistical significance. For example, seven of the 18 annual coefficient estimates for Los Angeles are positive and 11 are negative (counts are depicted on the left-hand axis). This pattern of both positive and negative MSA exposures is largely repeated in the other MSAs. The average coefficient for each MSA is also plotted in Panel B of Figure 3. These averages tend to center around zero (the right-hand axis), although we observe more variation from zero in the smaller MSAs. This figure clearly

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Hospitality (Orlando), Education and Health Services (Boston, Philadelphia), Natural Resources, Construction, and Manufacturing (Chicago, Indianapolis, Minneapolis, St. Louis, Los Angeles, Portland, Seattle, Houston, Detroit), and Trade, Transportation, and Utilities (Phoenix, Tampa, Atlanta, Denver, Kansas City, Dallas, Miami).

reveals why the average coefficient for most MSAs from our cross-sectional regressions cannot be distinguished from zero despite substantial year-to-year variation in the sign and magnitude of MSA exposures.

We plot in Panel C of Figure 3 the annual dispersion of the 25 MSA exposures. Although the MSA betas tend to center around zero, there is substantial variation across MSAs each year. Moreover, the location of individual MSAs in these scatter plots varies over time, consistent with the New York example presented in Panel A of Figure 3. The wide dispersion of the MSA betas from our Fama-MacBeth regressions implies abnormal returns may be available to REIT managers able to time entry into and out of MSAs.

The analysis presented above clearly establishes that MSA returns and REIT exposures vary significantly across MSAs and over time. We next examine the extent to which REIT mangers are able to time their investments in MSAs to take advantage of these variations in private market CRE returns. Traditional returns-based approaches to the analysis of market timing ability interpret increases in portfolio exposures to the market prior to periods of positive performance and decreases in exposure before performance declines as evidence of successful market timing by investment managers. For example, Merton and Henriksson (1981) develop a time series CAPM-based model that allows beta risk to be different in *ex post* "up" and "down" markets. More formally, the Merton-Henriksson market timing model is:

$$RET_{i,t} = \alpha_i + \beta_i r_{mkt,t} + \lambda_i Max(r_{mkt,t}, 0) + \varepsilon_{i,t}, \quad (5)$$

where $RET_{i,t}$ is the return on the portfolio (firm), and $r_{mkt,t}$ is the return on the market (or benchmark portfolio). The coefficient λ_i measures the portfolio manager's market timing ability. A positive and significant λ_i indicates that successful market timers exhibit significantly higher market beta exposures when the market subsequently performs well. In other words, the manager is able to accurately forecast positive market performance and acts on this forecast by shifting portfolio concentrations towards the market portfolio in anticipation of this expected positive performance.

We design a parametric test similar to Merton and Henriksson's (1981) market timing model using private CRE market return data as a proxy for performance at the MSA level. Our tests allow MSA beta risk to vary in high performing and low performing markets. In particular, we first identify whether a REIT's portfolio exposure to MSAs that subsequently perform well is associated with greater returns in the cross-section of firms. If firms are able to shift portfolio allocations towards high performing MSAs in a timely manner, then their returns should be more sensitive to their exposures to these markets.

Following Merton and Henriksson's (1981) concept of stock market timing, we sort the total return performance of the 25 MSAs into terciles in each year of our sample using realized NCREIF MSA level returns for that year. The NCREIF Property Index (NPI) tracks property-level quarterly returns on a large pool of properties acquired in the underlying private market in which equity REITs also invest. We construct our performance terciles using annual total returns disaggregated by property type and MSA.

We modify the framework of Merton and Henriksson by directly testing the impact on firm returns of portfolio exposures to the top performing markets in a panel data setting. More formally, our primary market timing specification is as follows:

$$RET_{i,t} = \alpha_i + \sum_{m}^{M} \beta_{i,m} r_{m,t} + \sum_{m}^{M} \lambda_{i,m} (r_{m,t}) HIPERF + \sum_{f}^{F} \beta_{i,f} X_{f,t} + \varepsilon_{i,t}, \tag{6}$$

where $RET_{i,t}$ is firm *i*'s excess return in year *t*, and α_i is a constant. $r_{m,t}$ is the property-type-specific NCREIF NPI return in the m^{th} MSA in year *t*, and $\beta_{i,m}$ is the sensitivity of firm *i*'s excess return to the NPI return in the m^{th} MSA. The second summation in equation (6) is constructed to capture the incremental sensitivity of firm *i*'s return to the property-type-specific NCREIF NPI return in the m^{th} MSA—conditional on that MSA being in the top performing NPI return tercile. *HIPERF* is a dichotomous variable set equal to 1 in year *t* if the m^{th} MSA is in the top performing tercile in year *t*, and is zero otherwise. $\lambda_{i,m}$ captures the increased sensitivity of a REIT's return to its exposure to the m^{th} MSA when it is a high performing market.

The final summation in equation (6) captures return sensitivity to a set of *F* asset pricing control factors: the three Fama-French risk factors: *MKT*, *SMB*, *HML*, augmented by a return momentum factor, *MOM* (e.g., Fama and French 1996; Liew and Vassalou, 2000; Lettau and Ludvigson, 2001; Jegadeesh and Titman, 1993; Carhart, 1997); and Pastor and Stambaugh's (2003) market liquidity measure (*PSLIQ*).[10]

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[10] See Ken French's website: (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html). *MKT* is the value-weighted return in excess of the US Treasury. *SMB* ("small minus big") is designed to measure the additional return investors earned in a particular month by investing in companies with relatively small market capitalizations. This "size premium" is computed as the average return for the smallest 30 percent of stocks minus the average return of the largest 30 percent of stocks in that month. *HML* (high minus low) is designed to measure the "value premium" obtained by investing in companies with high book-to-market values. *HML* is computed as the average return for the 50 percent of stocks with the highest B/M ratio minus the average return of the 50

Similar to Merton and Henriksson's framework, the coefficient λ_m measures market timing ability among REITs with respect to the m^{th} MSA. More specifically, if the estimated value of λ_m is positive, it indicates that the total sensitivity ($\beta_m+\lambda_m$) of REIT returns to returns in the local private market ($r_{m,t}$) is greater than β_m when the m^{th} MSA outperforms. This indicates good market timing. Conversely, a negative coefficient estimate for λ_m indicates that REITs, on average, were less exposed to the m^{th} MSA in years when it outperformed. This is evidence of bad market timing.

We begin by estimating equation (6) with firm fixed-effects for our 18-year sample period. We report λ estimates pertaining to each MSA in column (1) of Table 5. The estimated λ coefficient for New York is -0.454 with a p-value equal to 0.050. The interpretation is as follows. In years in which New York is in the upper tercile of performance (based on NCREIF NPI returns), the estimated beta for New York decreases by 0.454. That is, REIT returns are less sensitive (i.e., exposed) to New York when New York CRE is performing well. This is indicative of negative market timing ability among REIT managers. In contrast, the estimated λ for L.A. is 0.940 and is highly significant. This indicates REIT returns are more sensitive (exposed) to L.A. when L.A. CRE is performing well, which suggests positive market timing ability.

Inspection of column 1 in Table 5 reveals that REIT managers as a group exhibited some ability to increase portfolio sensitivity to MSAs that outperformed over the next year; that is, the estimated λ is positive and significant at the 10 percent level or greater for nine of the 25 MSAs. In addition to L.A., the remaining eight MSAs are Philadelphia, Dallas, Seattle, Orlando, Minneapolis, San Diego, Phoenix, and Indianapolis. However, in addition to New York, REIT managers actually had significantly less exposure to seven MSAs that subsequently outperformed over the next year: Chicago, San Francisco, Detroit, Houston, Tampa, Portland, and Sacramento. With respect to the six Gateway MSAs, REITs as a group were able to consistently time up markets only in L.A. They displayed negative ability to time New York, Chicago, and San Francisco. Clearly, the ability to time markets is concentrated in non-Gateway markets. Overall, the ability to time up markets has varied significantly across MSAs.

percent of stocks with the lowest B/M ratio each month. *MOM* is the average return on high prior return portfolios minus the average return on low prior return portfolios.

Positive market timing can also be attributed to a manager's ability to allocate less to poor performing markets before performance declines. We therefore test the impact on firm returns of geographic portfolio exposures to the under-performing markets in our panel data setting using the following regression model:

$$RET_{i,t} = \alpha_i + \sum_{m}^{M} \beta_{i,m} r_{m,t} + \sum_{m}^{M} \lambda_{i,m}(r_{m,t}) LOPERF + \sum_{f}^{F} \beta_{i,f} X_{f,t} + \varepsilon_{i,t}. \tag{7}$$

The second summation in equation (7) captures the incremental sensitivity of firm i's return to the property-type-specific NCREIF NPI return in the m^{th} MSA when that MSA is in the lowest performing NPI return tercile. *LOPERF* is a dichotomous variable set equal to 1 in year t if the m^{th} MSA is in the worst performing tercile in year t, and is zero otherwise. In this specification, $\lambda_{i,m}$ captures the increased sensitivity of a REIT's returns to its exposure to the worse performing MSAs. A negative coefficient estimate for λ_m indicates that REITs, on average, were less exposed to the m^{th} MSA in years when it underperformed. This is evidence of good market timing. A positive coefficient estimate for λ_m indicates that REITs, on average, were more exposed to the m^{th} MSA in years when it underperformed, which is evidence of bad market timing ahead of poor market performance.

We estimate equation (7) with firm fixed-effects over our 18-year sample period. These results are reported in column (2) of Table 5. The estimated λ coefficient for New York is 0.827 with a p-value equal to 0.030. Thus, in years in which New York is in the lower tercile of performance, the estimated beta for New York increases by 0.827. REIT returns have been *more* sensitive (exposed) to New York when New York CRE is under-performing, which is again indicative of negative market timing ability among REIT managers. Although REIT managers were able to time entry into L.A. in years in which L.A. subsequently outperformed, the estimated λ coefficient for L.A. in down markets cannot be distinguished from zero. With the exception of San Francisco, REITs as a group revealed no ability to reduce allocations to the six gateway markets ahead of a deterioration in private market returns in these MSAs. In addition to San Francisco, the average REIT was, however, able to significantly decrease allocations to the following eight markets just prior to years in which they underperformed: Philadelphia, Dallas, Miami, Orlando, Minneapolis, Seattle, Phoenix, and Indianapolis. Six of these MSAs (Philadelphia, Dallas, Orlando, Minneapolis, Phoenix, and Indianapolis) were markets that REIT managers were also able to positively time in anticipation of high performance. In contrast, REITs were significantly more exposed to only three MSAs that subsequently underperformed.

These market timing results must be interpreted within the context of the market dynamics in which equity REITs buy and sell properties. Listed REIT shares provide investors with a relatively high degree of liquidity and relatively low transaction costs. However, REIT property acquisitions and dispositions generally take place in private CRE markets, which are characterized by high search and transaction costs and low liquidity.[11] After a transaction price has been agreed by the buyer and seller, the buyer is granted a "due diligence" period during which the buyer more closely inspects important deal parameters, such as in-place leases, construction quality and deferred maintenance, and environmental issues. This due-diligence period can last for several months and include renegotiations of the purchase price. Thus, even when purchasers have a high degree of local market knowledge and deal execution experience, the lag between decisions to enter a market and completed acquisitions of properties can be substantial.[12]

Additional complexities hamper entry into new markets. When entering a MSA, REITs must concern themselves with the potential information disadvantage they face given their relative lack of local market knowledge. REITs often attempt to overcome this information disadvantage by hiring local talent and/or by engaging in joint ventures with local market experts. A lack of scale economies is also a concern when entering new markets. Generally, there are fixed costs associated with acquiring local market knowledge and assembling and maintaining a management team. Efficiency is gained when these costs of market entry and ongoing management are amortized over a larger portfolio of assets. As a result, REITs generally prefer to hold portfolios of some minimum size in each market in which they have a presence. In summary, even if a REIT management team is able to identify mispricing in a MSA, the costs and delays associated with entering a new MSA make it difficult to take advantage of the perceived mispricing. The same costs and potential delays associated with entering new markets are faced by real estate private equity funds, high net worth investors, pension funds, and other private investment vehicles.

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[11] REITs do have the ability to purchase properties by acquiring other listed REITs.

[12] As an additional robustness check, we re-estimate our MSA market timing regressions utilizing two year performance measures to better understand whether our choice of return horizon limits our ability to identify positive market timing across MSAs. In contrast, our results reveal that managers exhibit less market timing ability over longer return horizons. This is consistent with generally well-functioning capital markets in which the impact of expectation shocks on prices is not persistent.

REITs face many of the same costs and delays when attempting to sell properties. Given these costs and frictions, including the cost of assembling a local management team, REITs may hesitate to move out of a MSA based on the expectation the MSA will underperform in the following year. In addition, REIT legislation discourages REITs from actively selling properties because they are required to pay a 100 percent tax on profits from the sale of "dealer" property. However, it can be difficult to determine if a REIT acted as a dealer in a particular transaction as the classification is generally transaction specific, not taxpayer specific. According to the IRS, a "safe harbor" exists under which a REIT can be assured the 100 percent excise tax will not apply on the disposition of a property if several conditions are met.[13] As Muhlhofer (2015), Hochberg and Muhlhofer (2016), and others have argued, these requirements may reduce the ability of REITs to engage in market timing that requires property sales.

Finally, recent research identifies behavioral explanations for why REIT managers are constrained in their ability to dispose of assets in the midst of a market downturn. For example, Crane and Hartzell (2010) and Bokhari and Geltner (2011) find evidence that REIT managers are prone to a disposition effect (or exhibit loss aversion); that is, they tend to hang onto properties that underperform with an unwillingness to recognize a realized loss. Eichholtz and Yonder (2015) provide an alternate explanation rooted in CEO overconfidence. Since an overconfident CEO believes that his decisions bring positive outcomes, he postpones selling a property until the outcome reaches his desired value. In either case, cognitive biases may partially explain the inability or desire of REITs to decrease allocations to MSAs that subsequently underperform. Despite these potential regulatory, market driven, and behavioral bias impediments to property sales, REITs as a group have displayed the ability to be less exposed to a number of MSAs that subsequently underperform.

In comparison to the related literature, it is also important to note that our market timing tests and results vary from those presented in complementary work by Hochberg and Muhlhofer (2016). While the aforementioned study finds little evidence of aggregate market timing ability among REIT managers using a non-parametric methodology, we document evidence of positive market timing ability, on average, in approximately a third of the 25

[13] A REIT can be assured the 100% excise tax will not apply if all of the following are true: the property was held for at least two years; aggregate capital expenditures on property during the two years prior to its sale were less than 30 percent of sale price; the REIT did not sell more than seven properties in the year and did not sell more than 10 percent of its assets (based on book value or fair market value, at the REIT's discretion). These safe harbor rules were revised as part of the Housing and Economic Recovery Act of 2008.

major MSAs using a parametric approach. The parametric framework we employ has several advantages. First, some non-parametric tests of market timing ability have been shown to have low power relative to parametric-based tests (Beebower and Varikooty, 1997). This problem may be exacerbated when the frequency of the timing measure is greater than the frequency of the fund returns (Goetzmann, Ingersoll, and Ivkovic, 2000). Since Hochberg and Muhlhofer (2016) derive rolling quarterly market timing measures using annual return and portfolio concentration differences in the underlying CRE funds, this may partially explain why they find little evidence of market timing ability in CRE markets.

Second, by construction Hochberg and Muhlhofer's market timing measure treats exposures to up and down markets symmetrically. More specifically, the non-parametric approach of reporting simple time-series averages of market timing measures assigns equal weights to changes in portfolio composition that correspond to periods of positive and negative performance. Treating these two effects equivalently may mask variation in timing ability in up versus down markets. Since our parametric approach allows the coefficients on our market timing variables to vary across up and down markets, we are able to accommodate for this potential asymmetric relation in our market timing tests.

Third, Hochberg and Muhlhofer's market timing measure is unable to capture the importance of a manager's (or investor mandated) geographic focus in determining market timing ability. Consider the scenario of a property portfolio concentrated in several MSAs within the southeast region of the U.S. This concentration reflects the manager's experience and knowledge of the southeast region as well as the expectations of equity investors and lenders that the manager will remain focused on markets in which she is thought to have a comparative information and transaction execution advantage. During periods in which MSAs on the west coast significantly outperform those in the southeast, Hochberg and Muhlhofer's market timing measure penalizes this manager for not shifting allocations to the west coast. In contrast, by allowing up to eight MSAs to be included in the top performing terciles of the underlying property market, our approach provides a more flexible definition of positive market timing that accommodates the preference among many REIT mangers and investors for geographically focused property portfolios.

Finally, our approach further extends Hochberg and Muhlohofer's aggregate market timing analysis to consider individual MSA market timing dynamics. In so doing, we provide evidence contrary to their finding that some positive market timing ability exists only among managers that operate property portfolios in more liquid geographic markets. More liquid markets are also less informationally opaque, which may limit the ability of investors to uncover potential mispricing of assets. In fact, the market timing results discussed above for the six gateway markets suggest it is *more* difficult to market time in the six MSAs considered to be the most liquid. Unlike smaller MSAs, these gateway MSAs attract substantial interest, research, and capital from foreign investors and large U.S. institutional investors. The well-documented focus on these gateway markets by well capitalized investors with large research budgets may reduce the ability of REIT investors to uncover mispricing and time entry and exit.

Firm-Level Determinants of Market Timing Ability

Although the average REIT manager's ability to time geographic market allocations varies across MSAs, we expect certain types of firms to be better suited to take advantage of market timing opportunities when they are perceived to exist. For example, the ability to enter new MSAs, and therefore strategically time MSA entry and exit, may be related to the extent to which the REIT is currently diversified geographically. That is, firms with a larger platform and more experience owning and operating properties in multiple markets, and with an implicit mandate from investors to do so, may be better positioned to quickly act on any perceived investment opportunities they identify in the 25 markets. To test this hypothesis, we first sort firms based on observed market timing ability in the top 25 MSAs within a particular year using property level data of REIT portfolios. Our property level data allows us to directly observe changes in geographic portfolio allocations by REIT managers that occur ahead of periods of high and low MSA performance. In particular, we construct *GOODTIMER*, a dichotomous variable set equal to 1 if a firm increases (decreases) its exposure to the top (bottom) performing markets by the end of the year preceding the high (low) relative performance, and zero otherwise.[14] We then estimate a panel logit model of *GOODTIMER* on a set of firm characteristics defined previously that includes *SIZE, MB, MOMENTUM, ILLIQ,* and *LEV*. We also utilize our property level data to construct a Herfindahl index for each REIT as a measure of firm-level geographic diversification. Following Hartzell et al. (2014), we define *GEO_DIVERS* as the negative Herfindahl index as of the beginning of the year. In other words, firms with greater portfolio diversification

[14] Our empirical results are robust to defining *GOODTIMER* using changes in asset allocations preceding high (low) performance that is defined over a two-year horizon.

have higher index values. Along with *GEO_DIVERS*, property type and year fixed effects are included in our panel logit regressions.

Table 6 presents odds ratios from our panel logit regressions. In column 1, we identify a significant relation between *GEO_DIVERS* and *GOODTIMER* (p-value = 0.005). Consistent with our hypothesis, an increase in geographic diversification increases the likelihood of a firm exhibiting good market timing ability. In particular, a one standard deviation increase in *GEO_DIVERS* makes the firm 3.3 times more likely to exhibit positive market timing ability. We also find that firms with greater leverage are less able to time market entry and exit. A standard deviation increase in leverage decreases the likelihood of being a good timer ahead of high MSA performance by approximately 90 percent. This is consistent with binding financial constraints prohibiting REIT managers from accessing capital precisely at the time attractive investment opportunities arise.[15] Finally, we provide some weak evidence that firms exhibiting greater return momentum are also more likely to exhibit positive market timing ability.

Positive market timing can be attributed to both a manager's ability to allocate more to high performing markets prior to performance increases and/or to allocate less to poor performing markets prior to performance declines. Moreover, we may expect differences in the types of firms that are able to reallocate their geographic exposure ahead of high and low MSA performance. For example, while firms with greater geographic diversification and less capital constraints may be better equipped to take advantage of market entry opportunities, firms may be willing to exit a market only if they have other attractive investment opportunities on the horizon, regardless of their portfolio composition or financial condition. To distinguish between these two market timing scenarios, we estimate two additional specifications that distinguish between market timing ability ahead of high versus low MSA performance. We define *GOODTIMER_HIGH* as an indicator variable set equal to 1 if a firm increases its exposure to the top performing markets ahead of high relative performance within a particular year, and zero otherwise. Similarly, *GOODTIMER_LOW* is an indicator variable set equal to 1 if a firm decreases its allocation to the bottom performing markets ahead of low relative performance within a particular year, and zero otherwise. We replace *GOODTIMER* with *GOODTIMER_HIGH* and *GOODTIMER_LOW* as our dependent

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[15] We replace *LEV* with the Kaplan and Zingales (1997) KZ-index score as an alternate measure of financial constraint and obtain similar results in an additional robustness check.

variables, respectively, and re-estimate our panel logit regressions. Odds ratios are presented in columns 2 and 3 of Table 6.

In column 2 of Table 6, we provide further evidence supporting our previous findings that geographic diversification and firm leverage are important determinants of market timing ability ahead of positive MSA performance. However, several new findings emerge when we isolate good market timing ahead of poor performing markets. In column 3 of Table 6, we document a statistically significant relation between *SIZE* and *GOODTIMER_DOWN*. In terms of economic significance, a one standard deviation increase in firm size decreases the likelihood of being a good timer ahead of poor MSA performance by over 30 percent. We also find that firms with greater *MB* are more likely to decrease allocations ahead of poor MSA performance. This is consistent with a manager's willingness to decrease exposure to a market as long as other viable investment opportunities are perceived to be available in other markets. Finally, we find that our previously documented relation between *MOMENTUM* and market timing ability is concentrated in low performing investment environments.

Taken together, our logit regression results support the conclusion that the ability to time entry into high performing markets is concentrated in REITs with bigger geographic footprints and less financial constraints, while the ability to time market exit is more highly correlated with firm size and perceived investment opportunities. Overall, these additional results extend recent work by Hochberg and Muhlhofer (2016) by identifying cross-sectional differences in a REIT's ability to successfully time geographic market entry and exit.

Market Timing and Excess Returns

As an alternate parametric market timing test, we utilize a calendar-time portfolio approach to examine whether managers that exhibit market timing ability in their geographic allocation decisions are able to generate significant abnormal returns in the long-run. We begin by classifying firms as a *Good Timer* if they increase (decrease) their exposure to the top (bottom) performing markets ahead of high (low) relative performance. *Bad Timers* increase (decrease) their exposure to the bottom (top) performing markets ahead of low (high) relative performance. Each firm is included in one of the two portfolios at the beginning of each year and remains in the *Good Timer* or *Bad Timer* portfolio for the next 12 months. We then calculate monthly value-weighted returns for each portfolio from 1997 through 2013. In addition to comparing portfolio performance across our two subgroups, we also benchmark our returns to market (*MKT*), size (*SMB*), book-to-market (*HML*), momentum (*MOM*), and liquidity (*PSLIQ*) portfolios.

Panel A of Table 7 reports descriptive statistics for each portfolio. The *Good Timer* portfolio outperforms the *Bad Timer* portfolio by nearly 40 basis points on a monthly basis. Unconditionally, managers who are able to anticipate positive performance in geographic markets, and proactively adjust their portfolio exposure accordingly, generate greater returns than those with poor market timing ability.

To more formally examine abnormal performance, we estimate calendar-time portfolio regressions in which monthly excess portfolio returns are regressed on contemporaneous monthly *MKT, SMB*, *HML*, *MOM* and *PSLIQ* factors. The regression model is:

$$r_{p,t} - r_{f,t} = \alpha_P + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 PSLIQ_t + \varepsilon_t , \qquad (8)$$

where $r_{p,t}$ is the portfolio return and $r_{f,t}$ is the risk free rate for that year (i.e., one-month Treasury Bill rate). In this specification, the intercept term (α) denotes the average monthly abnormal return for a particular portfolio. We begin by estimating this model separately for both the *Good Timer* and *Bad Timer* portfolios. Panel B of Table 7 provides the results of these calendar-time regressions. Even after controlling for traditional risk factors, we find a positive and statistically significant alpha (p-value=0.056) for the *Good Timer* portfolio. This result is also economically significant as the *Good Timer* portfolio generates abnormal returns of 0.6% monthly, or 7.2% on an annualized basis. This additional result supports the hypothesis that REIT managers are able to generate abnormal returns by proactively adjusting portfolio exposures in anticipation of positive geographic market performance. Alpha for the *Bad Timer* portfolio is insignificant, thereby suggesting that poor market timers are not penalized for their inability to take advantage of value-adding allocation decisions.

We also calculate the difference between the incremental alphas of the *Good Timer* and *Bad Timer* portfolios. We first calculate the difference in the monthly returns between the two portfolios. We then regress this series of monthly return differences on the five risk factors. The model is:

$$\begin{aligned} R_{GT,t} - R_{BT,t} = {} & (\alpha_{GT} - \alpha_{BT}) + (\beta_{1GT} - \beta_{1BT})MKT_t + (\beta_{2GT} - \beta_{2BT})SMB_t \\ & + (\beta_{3GT} - \beta_{3BT})HML_t + (\beta_{4GT} - \beta_{4BT})MOM_t + (\beta_{5GT} - \beta_{5BT})PSLIQ_t + \varepsilon_{p,t} . \end{aligned} \qquad (9)$$

The resulting estimate for the difference in alphas $(\alpha_{GT} - \alpha_{BT})$ represents the average monthly abnormal return for the *Good Timer* portfolio as compared to the *Bad Timer* portfolio. The results reported in Panel B of Table 7 confirm an economically and statistically significant (p-value=0.060) difference in returns between the *Good Timer* and *Bad Timer* sample portfolios. This result extends recent work by Hochberg and Mulhoffer (2016) by quantifying the excess return associated with the positive market timing ability of REIT managers

Conclusion

Using a large sample of individual commercial property holdings, this study examines the sensitivity of equity REIT returns to the time-varying MSA allocations of the firm's underlying property portfolio. To our knowledge, we are the first to quantify the extent to which *individual* MSA allocations affect the cross-section of CRE returns. After establishing the cross-sectional and time varying nature of geographic exposures, we also provide direct evidence of the ability of REIT managers to effectively time portfolio acquisitions and dispositions in anticipation of expected performance differences across MSAs. Furthermore, we identify cross-sectional differences in firm characteristics that best equip managers to take advantage of time-varying geographic market conditions.

To the extent the realized return performance of CRE portfolios is expected to be tightly linked to the location of the underlying properties, controlling for a firm's geographic exposures should improve our ability to explain the cross-section of REIT returns. In cross sectional return regressions along the lines of Fama-MacBeth (1973), controlling for firm-level allocations to the underlying property market in the 25 major MSAs increases the average adjusted R-square by 12 percentage points relative to our baseline specification without locational effects. This is an economically and statistically significant increase in explanatory power. Moreover, we document substantial cross-sectional and time-series variation in the ability of MSA exposures to explain the cross-section of REIT returns. The lack of a clear pattern in these MSA effects suggests that while MSA allocations matter in the return generating process, the return enhancing (or destroying) abilities of particular MSA allocations appear to change rapidly as local market information is incorporated into property values.

Given the observed cross-sectional and time-series variation in the ability of MSA exposures to explain the cross-section of REIT returns, we develop a parametric test of market timing ability in the spirit of Merton and Henriksson (1981). We contribute to the broader market timing literature by documenting the influence of time-varying portfolio allocations towards (away from) geographic markets that subsequently perform well (poorly). In particular, we find evidence that is consistent with REIT managers having the ability to both identify MSAs that will outperform in the following year and overcome the costs and delays associated with increasing allocations to these MSAs. We also find, however, that the ability to time allocation decisions is concentrated in non-Gateway markets and varies significantly across MSAs.

Furthermore, we add to the geographic market timing literature by documenting significant cross-sectional differences in the characteristics of firms that are able to deploy the resources needed to actively time property markets. In particular, the ability to time entry into high performing markets is concentrated in well diversified REITs and those with fewer financial constraints. That is, financially flexible firms with a larger platform and experience owning and operating properties in multiple markets are better positioned to quickly act on investment opportunities they identify in major MSAs. In contrast, the ability to time market exit is more highly correlated with a firm's perceived investment opportunities. Managers are more willing to decrease exposure ahead of poor performance as long as viable investment opportunities are perceived to be available in other markets. Taken together, our results highlight the importance of geographic exposures of property portfolios and the geographic allocation decisions of a portfolio manager on CRE returns.

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Figure 1: Gateway and Top 25 MSA Concentrations by Equity REITs

This figure plots the geographic concentrations of listed (equity REIT) commercial real estate portfolios in the following metropolitan statistical areas (MSAs) for all core property types over the 1996-2013 sample period: Atlanta, Boston, Chicago, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C. Concentrations are displayed for both gateway cities, defined as Boston, Chicago, Los Angeles, New York, San Francisco, and Washington, D.C., and all 25 MSAs. Listed REIT market concentrations are calculated using reported adjusted cost of each core property held by equity REITs within the 25 MSAs.

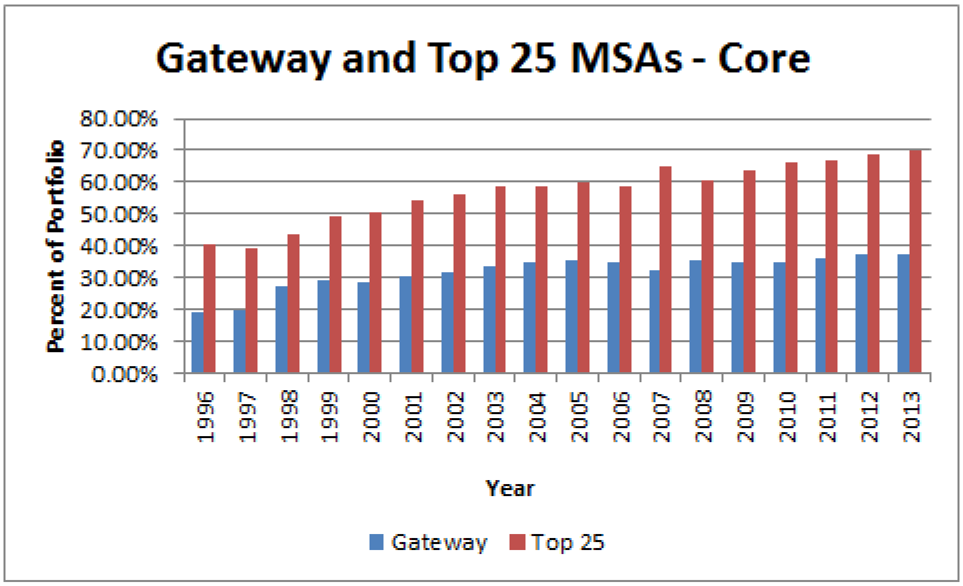


Figure 2: Core Property Returns by MSA

This figure plots the average and standard deviation of core property returns across metropolitan statistical areas (MSA) over the 1996-2013 sample period. MSAs include Atlanta, Boston, Chicago, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C. We utilize the NCREIF NPI index at the MSA level as our proxy for core property returns.

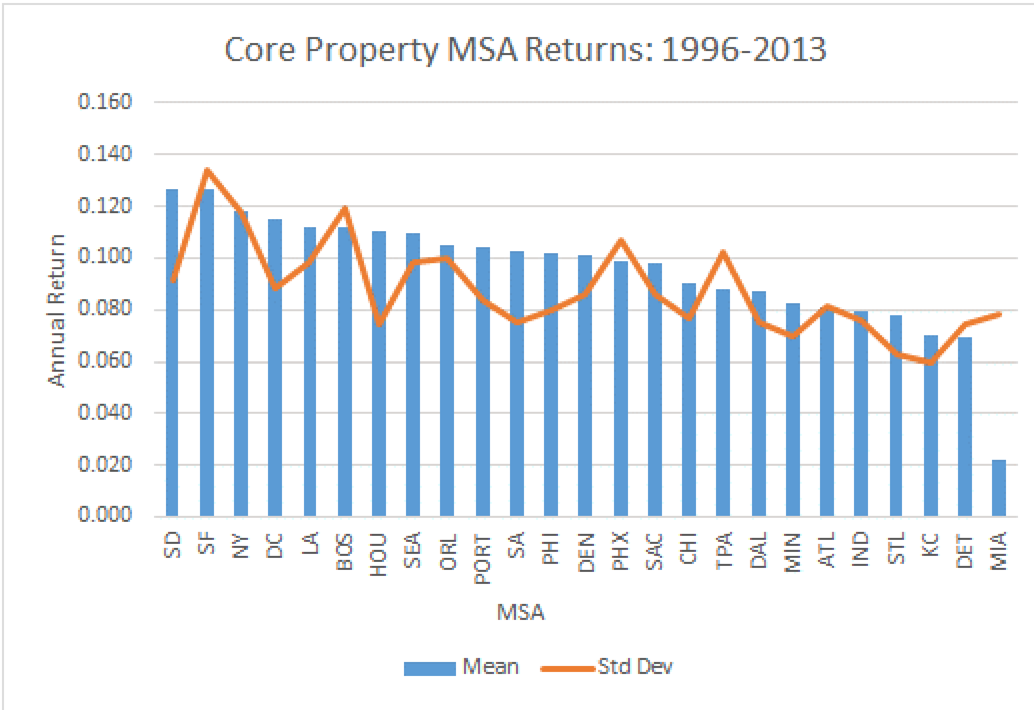
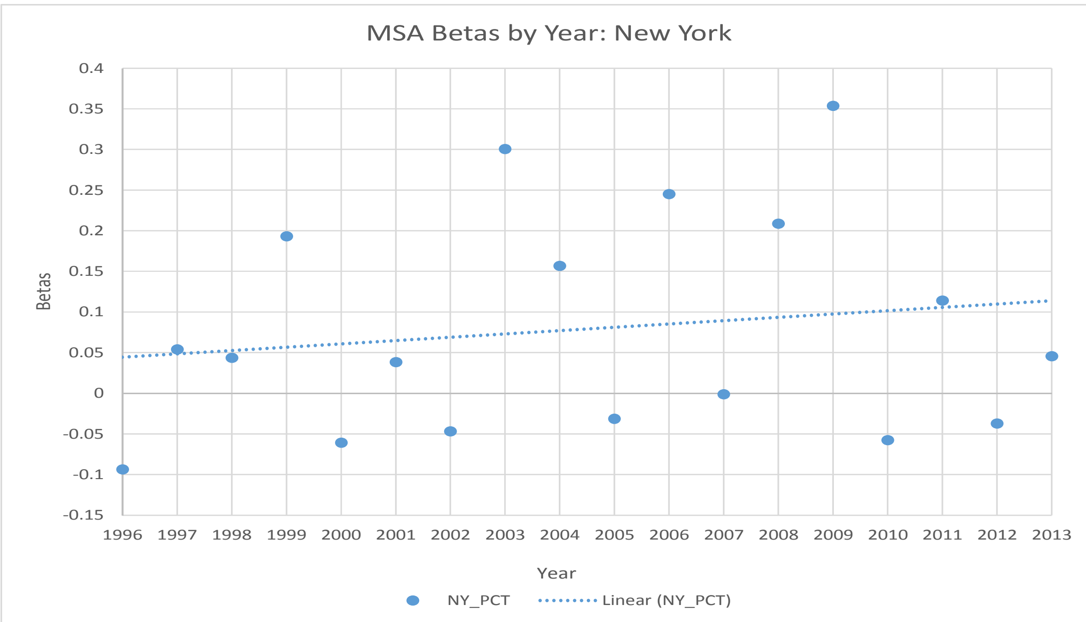


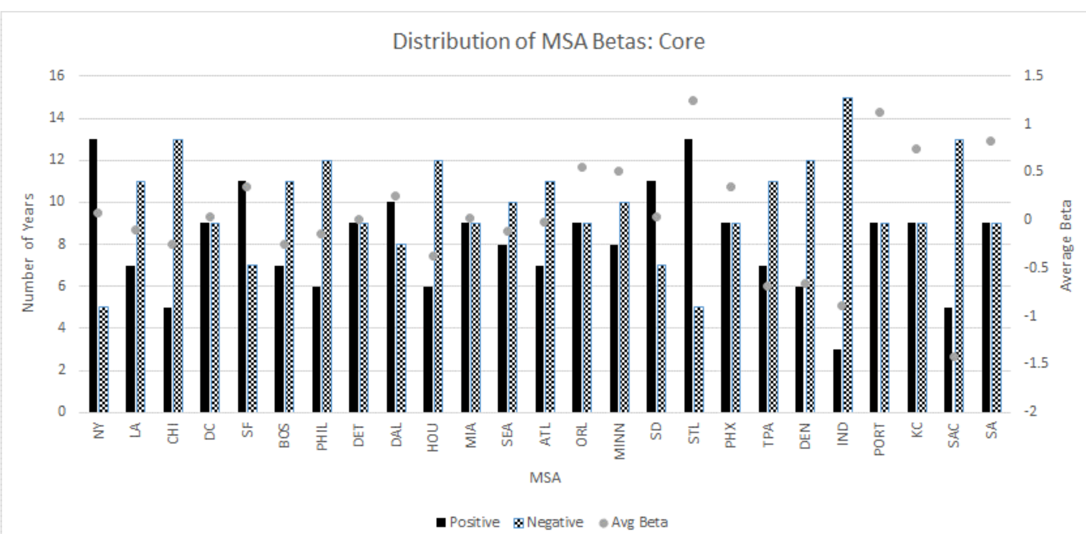
Figure 3: Distribution of Geographic Exposures

This figure plots time series and cross-sectional distributions of average geographic exposures of core equity REITs over the 1996-2013 sample period. Estimates are obtained from Fama-MacBeth regressions. MSAs include Atlanta, Boston, Chicago, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C.

Panel A: Time Series Distribution of MSA Betas – New York



Panel B: Cross-Sectional Distribution of MSA Betas



Panel C: Distribution of MSA Betas by Year and MSA

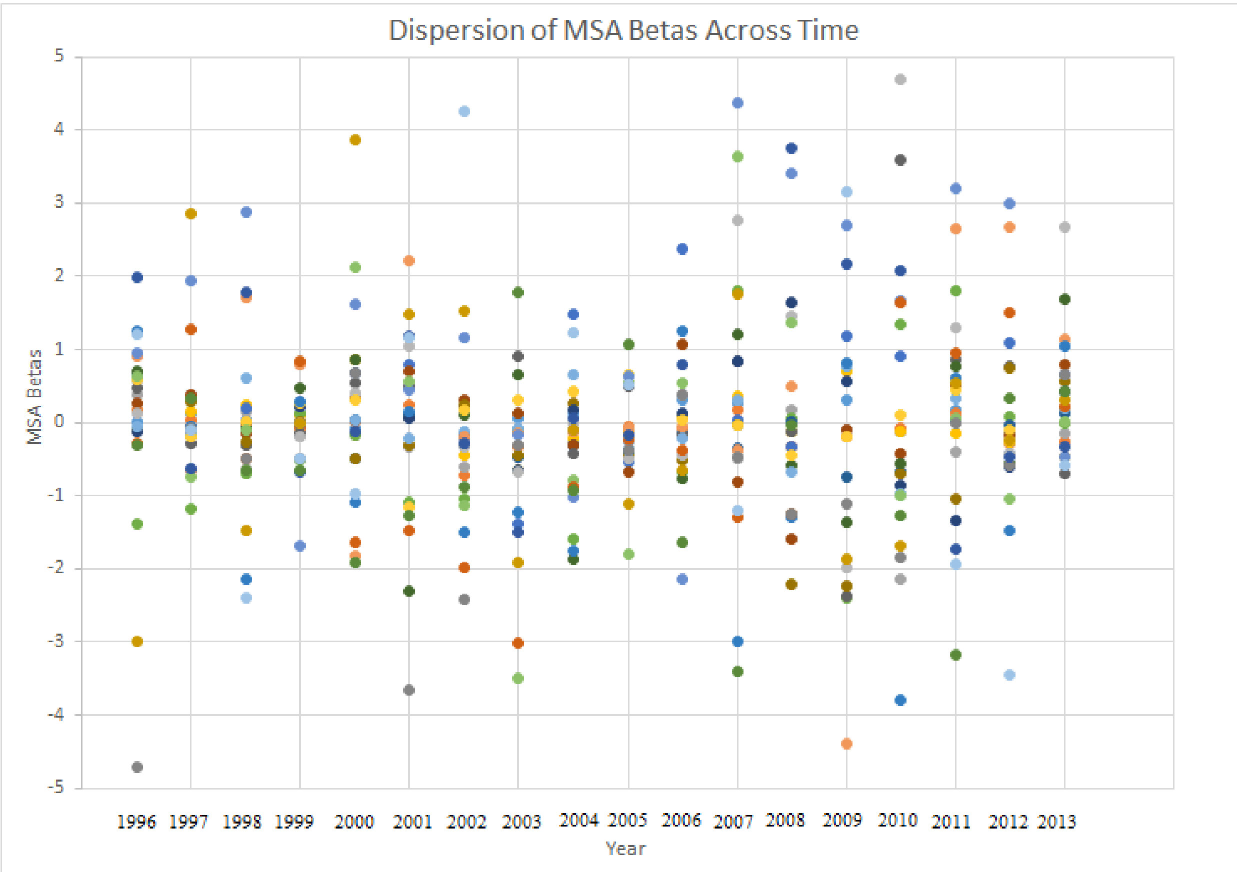


Table 1: Descriptive Statistics – Geographic Concentrations

This table reports descriptive statistics for our annual firm-level concentration measures for each of the following 25 MSAs: Atlanta, Boston, Chicago, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C. The sample period spans 1996-2013. The number of firm-year observations is 1,044.

	Mean	Median	Std Dev	Min	Max
NY	0.100	0.000	0.218	0.000	1.000
LA	0.067	0.000	0.168	0.000	1.000
DC	0.067	0.000	0.144	0.000	1.000
ATL	0.051	0.002	0.131	0.000	1.000
CHI	0.048	0.000	0.131	0.000	1.000
DAL	0.030	0.000	0.060	0.000	0.383
PHI	0.029	0.000	0.093	0.000	0.840
SF	0.027	0.000	0.067	0.000	0.633
MIA	0.023	0.000	0.055	0.000	0.567
SD	0.022	0.000	0.065	0.000	0.599
HOU	0.021	0.000	0.062	0.000	0.658
ORL	0.018	0.000	0.062	0.000	0.717
DET	0.017	0.000	0.049	0.000	0.450
SEA	0.015	0.000	0.039	0.000	0.322
PHX	0.015	0.000	0.037	0.000	0.485
TPA	0.014	0.000	0.029	0.000	0.253
DEN	0.013	0.000	0.034	0.000	0.515
BOS	0.013	0.000	0.035	0.000	0.317
MIN	0.012	0.000	0.052	0.000	0.714
IND	0.011	0.000	0.058	0.000	1.000
KC	0.006	0.000	0.020	0.000	0.147
PORT	0.005	0.000	0.021	0.000	0.444
STL	0.005	0.000	0.015	0.000	0.161
SAC	0.005	0.000	0.017	0.000	0.282
SA	0.004	0.000	0.013	0.000	0.112

Table 2: Descriptive Statistics – MSA Returns

This table reports descriptive statistics for annual NCREIF NPI returns disaggregated by MSA at the core property type level. Returns for the following MSAs are reported: Atlanta, Boston, Chicago, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C. The sample period spans 1996-2013.

	Mean	Median	Std Dev	Min	Max
SD	0.126	0.139	0.091	-0.139	0.263
SF	0.126	0.169	0.134	-0.243	0.278
NY	0.118	0.136	0.118	-0.219	0.283
DC	0.115	0.131	0.088	-0.124	0.259
LA	0.112	0.127	0.098	-0.188	0.214
BOS	0.112	0.138	0.119	-0.225	0.338
HOU	0.110	0.112	0.075	-0.102	0.237
SEA	0.109	0.142	0.099	-0.197	0.200
ORL	0.105	0.123	0.100	-0.160	0.325
PORT	0.104	0.117	0.083	-0.155	0.214
SA	0.103	0.108	0.075	-0.080	0.263
PHI	0.102	0.119	0.080	-0.146	0.198
DEN	0.101	0.130	0.086	-0.157	0.198
PHX	0.098	0.117	0.107	-0.210	0.297
SAC	0.098	0.111	0.086	-0.165	0.189
CHI	0.090	0.113	0.076	-0.138	0.160
TPA	0.088	0.091	0.103	-0.185	0.297
DAL	0.087	0.111	0.075	-0.147	0.152
MIN	0.083	0.097	0.070	-0.130	0.173
ATL	0.081	0.100	0.081	-0.174	0.163
IND	0.079	0.089	0.076	-0.176	0.147
STL	0.078	0.097	0.062	-0.106	0.170
KC	0.070	0.088	0.060	-0.096	0.136
DET	0.069	0.075	0.074	-0.138	0.186
MIA	0.022	0.034	0.078	-0.190	0.124

Table 3: Summary Statistics- Firm Characteristics

This table presents descriptive statistics of firm characteristics for the full sample of equity REITs during the 1996-2013 sample period. RET is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill. *SIZE* is the natural log of the firm's aggregate market capitalization. *M/B* is the market value of assets divided by the book value of assets. *MOMENTUM* is the firm's cumulative return over the prior year. *ILLIQ* is the natural logarithm of the stock's Amihud (2002) illiquidity measure. *LEV* is total debt divided by the book value of total assets. Percentages are expressed in decimal form. The number of firm-year observations is 1,044.

	Mean	Median	Std Dev.	Min	Max
RET	0.129	0.134	0.265	-0.951	1.170
SIZE	1.655	0.812	2.450	0.005	19.900
M/B	1.841	1.840	0.466	0.670	3.771
MOMENTUM	0.068	0.069	0.256	-0.950	0.939
ILLIQ	-5.159	-5.480	2.440	-11.377	4.058
LEV	0.421	0.416	0.156	0.000	0.937

Table 4: Panel Regression and Fama-MacBeth Estimation

This table reports results from panel regressions and Fama-MacBeth estimations examining the impact of geographic market exposure on the cross-section of core equity REIT returns. The dependent variable, *RET* is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill. *SIZE is* the natural log of the firm's aggregate market capitalization. *M/B* is the market value of assets divided by the book value of assets. *MOMENTUM* is the firm's cumulative return over the prior year. *ILLIQ* is the natural logarithm of the stock's Amihud (2002) illiquidity measure. *LEV* is total debt divided by the book value of total assets; *CON_GATEWAY* is the percentage of a firm's total property portfolio located in gateway markets defined as Boston, Chicago, Los Angeles, New York, San Francisco, and Washington, D.C. *CON*, is the percentage of a firm's total property portfolio located in top 25 markets defined as Atlanta, Boston, Chicago, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C. We also construct portfolio concentrations in each of these individual markets for each REIT. All portfolio concentrations are calculated using adjusted cost measures obtained from SNL. All regressions include property type fixed-effects. *N* is the number of firm-year observations. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013

	Panel Regression				*Fama-MacBeth*			
	RET	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*
SIZE	-0.131***	-0.138***	-0.140***	-0.160***	-0.073***	-0.079***	-0.076***	-0.069**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.003)	(0.002)	(0.022)
MB	-0.085***	-0.101***	-0.087***	-0.099***	0.015	0.009	0.020	0.020
	(0.005)	(0.000)	(0.002)	(0.000)	(0.507)	(0.687)	(0.363)	(0.483)
MOMENTUM	0.064**	0.057*	0.062*	0.057*	0.137***	0.132***	0.131**	0.126*
	(0.049)	(0.063)	(0.051)	(0.059)	(0.007)	(0.007)	(0.014)	(0.071)
ILLIQ	-0.088***	-0.092***	-0.092***	-0.101***	-0.048***	-0.052***	-0.050***	-0.041*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.002)	(0.001)	(0.020)
LEV	0.185***	0.192***	0.186***	0.206***	0.062	0.072	0.054	0.127
	(0.005)	(0.005)	(0.006)	(0.006)	(0.416)	(0.358)	(0.480)	(0.199)
CON_GATEWAY	-	0.101**	-	-	-	0.047**	-	-
	-	(0.017)	-	-	-	(0.047)	-	-
CON	-	-	0.086*	-	-	-	0.026	-
	-	-	(0.081)	-	-	-	(0.411)	-
CON_NY	-	-	-	0.183**	-	-	-	0.079**
	-	-	-	(0.015)	-	-	-	(0.030)
CON_LA	-	-	-	0.026	-	-	-	-0.094*
	-	-	-	(0.665)	-	-	-	(0.089)
CON_CHI	-	-	-	-0.001	-	-	-	-0.245*
	-	-	-	(0.992)	-	-	-	(0.060)
CON_DC	-	-	-	0.143	-	-	-	0.033
	-	-	-	(0.161)	-	-	-	(0.703)
CON_SF	-	-	-	0.200*	-	-	-	0.349*
	-	-	-	(0.075)	-	-	-	(0.093)
CON_BOS	-	-	-	0.289	-	-	-	-0.250
	-	-	-	(0.228)	-	-	-	(0.354)
CON_PHIL	-	-	-	-0.021	-	-	-	-0.145*
	-	-	-	(0.790)	-	-	-	(0.056)
CON_DET	-	-	-	-0.146	-	-	-	0.015
	-	-	-	(0.209)	-	-	-	(0.919)
CON_DAL	-	-	-	-0.100	-	-	-	0.260
	-	-	-	(0.556)	-	-	-	(0.333)
CON_HOU	-	-	-	-0.214*	-	-	-	-0.368*
	-	-	-	(0.071)	-	-	-	(0.054)
CON_MIA	-	-	-	0.128	-	-	-	0.019
	-	-	-	(0.317)	-	-	-	(0.905)
CON_SEA	-	-	-	0.213	-	-	-	-0.116
	-	-	-	(0.207)	-	-	-	(0.641)

Table 4: Cont'd

	Panel Regression				Fama-MacBeth			
	RET	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*
CON_ATL	-	-	-	0.036	-	-	-	-0.015
	-	-	-	(0.542)	-	-	-	(0.887)
CON_ORL	-	-	-	0.150**	-	-	-	0.548
	-	-	-	(0.026)	-	-	-	(0.249)
CON_MIN	-	-	-	0.100	-	-	-	0.513
	-	-	-	(0.387)	-	-	-	(0.170)
CON_SD	-	-	-	0.210**	-	-	-	0.041
	-	-	-	(0.020)	-	-	-	(0.691)
CON_STL	-	-	-	0.567	-	-	-	1.252***
	-	-	-	(0.357)	-	-	-	(0.004)
CON_PHX	-	-	-	0.259	-	-	-	0.343
	-	-	-	(0.284)	-	-	-	(0.548)
CON_TPA	-	-	-	0.210	-	-	-	-0.682**
	-	-	-	(0.497)	-	-	-	(0.050)
CON_DEN	-	-	-	0.353	-	-	-	-0.657
	-	-	-	(0.251)	-	-	-	(0.110)
CON_IND	-	-	-	-0.035	-	-	-	-0.895***
	-	-	-	(0.884)	-	-	-	(0.008)
CON_PORT	-	-	-	0.363	-	-	-	1.128
	-	-	-	(0.428)	-	-	-	(0.341)
CON_KC	-	-	-	0.210	-	-	-	0.738*
	-	-	-	(0.597)	-	-	-	(0.090)
CON_SAC	-	-	-	-0.719*	-	-	-	-1.414*
	-	-	-	(0.083)	-	-	-	(0.065)
CON_SA	-	-	-	0.458	-	-	-	0.827
				(0.409)				(0.325)
Constant	1.519***	1.599	1.574	1.809***	0.797***	0.855***	0.803***	0.759**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.003)	(0.003)	(0.016)
PType Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.10	0.11	0.11	0.11	0.23	0.24	0.24	0.35
N	1044	1044	1044	1044	1044	1044	1044	1044

Table 5: Market Timing Ability – Parametric Tests

This table reports panel regression results from parametric market timing tests examining the average market timing ability of REIT managers across the top 25 MSAs defined as: Atlanta, Boston, Chicago, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C. We estimate two regression specifications constructed in the spirit of Merton and Henriksson (1981) to identify market timing ability in anticipation of high and low MSA performance. The analysis of market timing ahead of periods of high performance takes the following form:

$$RET_{i,t} = \alpha_i + \sum_{m}^{M} \beta_{i,m} r_{m,t} + \sum_{m}^{M} \lambda_{i,m}(r_{m,t}) HIPERF + \sum_{f}^{F} \beta_{i,f} X_{f,t} + \varepsilon_{i,t},$$

The analysis of market timing ahead of periods of low performance takes the following form:

$$RET_{i,t} = \alpha_i + \sum_{m}^{M} \beta_{i,m} r_{m,t} + \sum_{m}^{M} \lambda_{i,m}(r_{m,t}) LOPERF + \sum_{f}^{F} \beta_{i,f} X_{f,t} + \varepsilon_{i,t},$$

where *RET* is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill; $r_{m,t}$ is the property-type-specific NCREIF NPI return in the m^{th} MSA in year t and $\beta_{i,m}$ is the sensitivity of firm i's excess return to the NPI return in the m^{th} MSA. *HIPERF* is a dichotomous variable set equal to 1 in year t if the m^{th} MSA is in the top performing tercile in year t, and is zero otherwise. *LOPERF* is a dichotomous variable set equal to 1 in year t if the m^{th} MSA is in the bottom performing tercile in year t, and is zero otherwise. $X_{f,t}$ includes the following set of controls: the three Fama-French risk factors (*MKT, SMB*, and *HML*) augmented by momentum (*MOM*), and Pastor and Stambaugh's market liquidity measure (*PS_LIQ*). Regressions include ~~property type~~firm fixed-effects. *N* is the number of firm-year observations. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013.

	HIPERF	*LOPERF*
	RET	*RET*
λ_NY	-0.454**	0.827**
	(0.050)	(0.030)
λ_LA	0.940***	-0.266
	(0.004)	(0.492)
λ_CHI	-1.282**	-0.312
	(0.033)	(0.353)
λ_DC	-0.235	-0.164
	(0.206)	(0.741)
λ_SF	-0.477***	-1.068***
	(0.003)	(0.002)
λ_BOS	0.010	-0.211
	(0.970)	(0.511)
λ_PHIL	0.581*	-0.775**
	(0.065)	(0.046)
λ_DET	-0.673*	0.410
	(0.066)	(0.254)
λ_DAL	0.749***	-0.490*
	(0.002)	(0.068)
λ_HOU	0.056	0.583**
	(0.832)	(0.016)
λ_MIA	-0.279	-0.768**
	(0.405)	(0.011)
λ_SEA	0.777**	0.358
	(0.016)	(0.245)
λ_ATL	0.315	-0.133
	(0.390)	(0.736)
λ_ORL	1.725***	-0.760***
	(0.000)	(0.005)
λ_MIN	1.448***	-1.019***
	(0.001)	(0.000)

Table 5: Cont'd

	HIPERF	*LOPERF*
	RET	*RET*
λ_SD	0.955***	1.249***
	(0.001)	(0.002)
λ_STL	-0.787	-0.548*
	(0.101)	(0.095)
λ_PHX	0.944***	-0.816***
	(0.002)	(0.009)
λ_TPA	-1.279***	-0.072
	(0.000)	(0.850)
λ_DEN	-0.203	-0.125
	(0.520)	(0.729)
λ_IND	1.327**	-0.635*
	(0.030)	(0.062)
λ_PORT	-0.453**	-0.228
	(0.025)	(0.310)
λ_KC	0.344	0.068
	(0.424)	(0.809)
λ_SAC	-1.305**	0.086
	(0.015)	(0.746)
λ_SA	1.008	-0.506
	(0.112)	(0.128)
Constant	-0.078**	-0.141***
	(0.018)	(0.004)
Firm Fixed Effects	Yes	Yes
Adjusted R^2	0.52	0.52
N	1044	1044

Control Variables: MKT, SMB, HML, MOM, PS_LIQ, NY_RET, LA_RET, CHI_RET, DC_RET, SF_RET, BOS_RET, PHIL_RET, DET_RET, DAL_RET, HOU_RET, MIA_RET, SEA_RET, ATL_RET, ORL_RET, MIN_RET, SD_RET, STL_RET, PHX_RET, TPA_RET, DEN_RET, IND_RET, PORT_RET, KC_RET, SAC_RET, SA_RET

Table 6: Determinants of Market Timing Ability – Panel Logit Regressions

This table reports results from panel logit regressions examining the cross-sectional determinants of market timing ability by REIT managers. Our primary dependent variable, *GOODTIMER*, is a dichotomous variable set equal to 1 if a firm increases (decreases) its exposure to the top (bottom) performing markets by the end of the year preceding the high (low) relative performance, and zero otherwise. *GOODTIMER_HIGH* is an indicator variable set equal to 1 if a firm increases its exposure to the top performing markets ahead of high relative performance within a particular year, and zero otherwise. *GOODTIMER_LOW* is an indicator variable set equal to 1 if a firm decreases its allocation to the bottom performing markets ahead of low relative performance within a particular year, and zero otherwise. *SIZE is* the natural log of the firm's aggregate market capitalization. *M/B* is the market value of assets divided by the book value of assets. *MOMENTUM* is the firm's cumulative return over the prior year. *ILLIQ* is the natural logarithm of the stock's Amihud (2002) illiquidity measure. *LEV* is total debt divided by the book value of total assets. *GEO_DIVERS* is the negative Herfindahl index of a REIT's geographic portfolio as of the beginning of the year. Property type fixed effects and time year fixed effects are also included in each specification. *N* is the number of firm-year observations. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013.

	GOODTIMER	*GOODTIMER_HIGH*	*GOODTIMER_LOW*
SIZE	0.931	1.077	0.681**
	(0.712)	(0.696)	(0.017)
MB	1.424	1.283	4.134***
	(0.109)	(0.252)	(0.000)
MOMENTUM	2.185*	1.459	2.302**
	(0.090)	(0.397)	(0.035)
ILLIQ	0.914	0.918	0.911
	(0.502)	(0.519)	(0.374)
LEV	0.101***	0.139***	0.696
	(0.000)	(0.001)	(0.469)
GEO_DIVERS	3.339***	5.821***	0.639
	(0.005)	(0.000)	(0.233)
Log Likelihood	-486.36	-520.30	-448.71
Property Type Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	1044	1044	1044

Table 7: Calendar Time Portfolio Regressions by Market Timing Ability

This table reports results from calendar time portfolio regressions. *Good Timer Portfolio* is the value-weighted return on the portfolio of firms that either increased their exposure to high performing markets or decreased their exposure to low performing markets. *Bad Timer Portfolio* is the value-weighted return on the portfolio of firms that either increased their exposure to low performing markets or decreased their exposure to high performing markets. Portfolio returns are constructed using monthly returns. Firms are sorted into High, Mid, and Low tercile portfolios at the beginning of each year. The calendar time regression model is as follows:

$$r_{p,t} - r_{f,t} = \alpha_P + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 PS\_LIQ_t + \varepsilon_t$$

where $r_{p,t}$ is the equal-weighted portfolio return and $r_{f,t}$ is the risk-free rate (yield on the 1-month Treasury Bill). The set of control variables in our calendar time portfolio regressions are the three Fama-French risk factors (*MKT*, *SMB*, and *HML*) augmented by momentum (*MOM*), and Pastor and Stambaugh's market liquidity measure (*PS_LIQ*). P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013.

Panel A: Portfolio Returns

	Mean	Median	SD	Min	Max
Good Timer Portfolio	0.014	0.018	0.062	-0.354	0.312
Bad Timer Portfolio	0.010	0.016	0.063	-0.283	0.288
MKT	0.005	0.013	0.048	-0.172	0.114
SMB	0.003	0.001	0.036	-0.167	0.223
HML	0.003	0.002	0.034	-0.131	0.139
MOM	0.004	0.006	0.057	-0.346	0.184
PS_LIQ	0.000	0.003	0.070	-0.271	0.287

Panel B: Calendar Time Portfolio Regressions

	α	*MKT*	*SMB*	*HML*	*MOM*	*PS_LIQ*
Good Timer Portfolio	0.006*	0.778***	0.476***	0.886***	-0.081***	-0.170***
	(0.056)	(0.000)	(0.000)	(0.000)	(0.160)	(0.000)
Bad Timer Portfolio	0.002	0.853***	0.401***	0.932***	-0.102*	-0.166***
	(0.401)	(0.000)	(0.000)	(0.000)	(0.065)	(0.000)
GOOD-BAD	0.003*	-0.075*	0.075	-0.065	0.020	-0.003
	(0.060)	(0.085)	(0.172)	(0.256)	(0.554)	(0.902)