Asset Productivity, Local Information Diffusion, and Commercial Real Estate Returns*

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Abstract

The geography of a firm's assets is an important determinant of its investment decisions and productivity, which, in turn, drives stock returns. We construct a novel measure of the returns earned by private market investors in the metropolitan areas where each equity REIT owns properties. We then risk-adjust this geographically weighted proxy for each REIT's property portfolio return (*PPR*) by regressing it against the sensitivity of the REIT's returns to systematic risk factors. We find that this risk-adjusted property portfolio return (αPPR) predicts the cross-section of returns in the public REIT market, suggesting a slow diffusion of asset-level information into stock returns. Our findings also suggest it is the slow diffusion of information about "local" prices changes, not current rental income or local liquidity, that predicts REIT returns. Moreover, the *aPPR*s associated with REIT allocations to major "gateway" markets are more predictive of REIT returns than the property portfolio returns produced by allocations to secondary and tertiary markets. This study improves our understanding of the extent to which "local" information about the productivity of a firm's assets is capitalized into stock prices and the speed at which it is capitalized. This study also contributes to the literature on the predictability of REIT returns and the relation between private and public CRE returns using firm-level, instead of index level, returns.

Keywords: Commercial real estate returns, Local information diffusion, Return predictability, REITs

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1. Introduction

Movements in a firm's stock price are largely driven by the perceived productivity of its underlying assets, which is difficult to observe and measure. The literature uses various proxies for a firm's productivity, such as firm size, age, and the ratio of a firm's stock price to the book value of its assets. A growing literature recognizes that the geography of a firm's assets is also an important determinant of its investment decisions, asset productivity, and stock returns. For example, Smajlbegovic (2019) finds that economic activity in regions that are economically relevant to a company helps predict the cross-section of stock returns and Addoum et al. (2017) find that the performance of other firms located in regions that are economically relevant to a firm helps predict the firm's earnings and cash flows. However, new information about "local" economic activity that is relevant to a firm's stock price may not be immediately observable to the marginal investor of that stock. This gradual diffusion of economically relevant local information into stock prices could generate persistent return predictability in the cross-section of equity returns.

Examination of the extent to which local information about the productivity of a firm's underlying assets is capitalized into stock prices requires two sets of information: (1) accurate information about the locations and magnitudes of a firm's economic interests (i.e., its geographic "footprint") and (2) an accurate measure of the economic activity in those areas thought to be relevant for the firm. Several recent papers have recognized the limitation of using the location of a firm's headquarters as a proxy for the geographic distribution of its economic interests and activities (e.g., Garcia and Norli, 2012; Bernile et al., 2015; Ling et al., 2019b). As an alternative, Garcia and Norli (2012) and Bernile et al. (2015) employ a text-based approach to infer a firm's geographic footprint by tabulating the number of times a U.S. state's name appears in the firm's 10-K. These state counts are used to determine the share of 10-K citations earned by each state.[1]

To capture the economic environment to which a firm's assets are exposed, the finance literature has used indices of local economic activity. For example, Korniotis and Kumar (2013) create a state-level economic activity index for the headquarters state of a firm that incorporates state income growth, state housing prices, and unemployment. Smajlbegovic (2019) adopts similar state-level indexes and multiplies them by the 10-K citation shares for

[1] For example, if Michigan is mentioned three times in a 10-K report, Indiana two times, and Delaware five times, a text-based approach would conclude that 50 percent of the firm's economic activity occurs in Delaware, 30 percent in Michigan, and 20 percent in Indiana.

each state to determine a weighted average measure of each firm's exposure to "local" economic activity. This approach is repeated quarterly or annually to produce a time series of each firm's exposure to local (state-level) economic activity.

Although generalizable to multiple industry sectors, these methods have limitations. State counts (citations) implicitly assume states with different sizes and economic relevance are identical. The use of states as the unit of measure for geography also masks the potential variation across metropolitan areas *within* a state. In addition, these state-level indices of economic activity may not be highly correlated with the underlying productivity of a firm's capital, labor, and management in a local area. The measurement error associated with this constructed variable is likely to be larger for firms that employ less labor (more capital) in their production function or have a relatively high percentage of (difficult to value) intangible assets. Moreover, the number of times a particular state's name is mentioned in a firm's 10-K report may not directly identify the state's economic significance to the firm.[2] In addition, the state economic activity indices used in these studies are complex by construction, which might hinder the interpretation of their economic meaning (e.g., how does one interpret a 1% increase in a state's economic activity?).

We improve on both the measurement of a firm's geographic footprint and the measurement of economically relevant activity by focusing our analysis on publicly traded real estate investment trusts (REITs). A "qualified" REIT may deduct dividends paid from corporate taxable income if they satisfy a set of restrictive conditions on an ongoing basis. For our analysis, the most important of these restrictions is that fully 75% of the value of the REIT's assets must consist of real estate assets, cash, and government securities. Moreover, at least 75% of the REIT's gross income must be derived from real estate assets. These two requirements ensure that REITs invest primarily in real estate. Such tangible real assets are relatively easier to locate and value than the properties, factories, equipment, and intangible assets of most non-real estate firms. This provides a relatively clean setting for identifying the channel through which private information about local economic activity diffuses to the stock market.

[2] As just one example, consider a situation in which two states are mentioned the same number of times in a firm's 10-K report and are therefore given equal weights as locations of the firm's economic activity. However, if the firm plans to close operations in the first state but expand operations in the second, a 10-K based measure of this firm's economic activity would clearly overweight the economic importance of the first state relative to the second.

We first measure a firm's asset portfolio exposure to each metropolitan statistical area (MSA) in the U.S. at the beginning of each year from 1996 to 2018. For each property held by each equity REIT, the S&P Global Real Estate Properties database (formerly SNL Real Estate) provides information on its property type (e.g., office versus retail), MSA location, and several measures of property value. This information allows us to accurately construct time-varying measures of each REIT's geographic concentration in each MSA.

Second, we take advantage of an important feature of commercial real estate (CRE) markets to measure the productivity of a firm's underlying assets. The market value and cash flows generated by an industrial firm's plant and equipment or a technology firm's patents and research under development are difficult to estimate. However, equity REITs typically acquire and dispose of CRE in an active "parallel" private market. Moreover, the private market property transactions of equity REITs and other market participants are recorded and compiled by several firms and industry associations. For example, the National Council of Real Estate Investment Fiduciaries (NCREIF) provides quarterly estimates of the total unlevered returns earned by institutional owners of a wide variety of property types in over 300 metropolitan markets. Using these quarterly MSA-property-type-level NCREIF returns and the MSA portfolio weights obtained from S&P Global data, we construct a novel time-series proxy for the returns on each REIT's underlying property portfolio (*PPR*).

Because these raw *PPRs* capture both systematic and idiosyncratic risk, we construct two risk-adjusted *PPR*s. Following an approach similar to Smajlbegovic (2019), we orthogonalize our quarterly estimates of raw *PPR* against the sensitivity of equity REIT returns to private CRE market returns at the national level, to private CRE market turnover (liquidity) at the national level, as well as to standard firm-level risk proxies. This process produces a quarterly time-series of risk-adjusted alphas, αPPRs, for each REITs. Lastly, it may still be possible that the ability of lagged αPPRs to predict returns is due to omitted variables that are correlated with local market economic activity. We therefore orthogonalize αPPR against a measure of local economic activity and obtain our third *PPR* measure, $O\alpha PPR$, which captures idiosyncratic private information about local property markets.

To examine the relationship between *PPR* and REIT returns, we first sort REITs into *PPR* (or αPPR) terciles (low, medium and high) at the beginning of each period, rebalancing the constituents of the three portfolios at the beginning of each period based on *PPR*s in the prior period. Using quarterly data, a portfolio strategy of taking a long position in the highest tercile *PPR* (αPPR) firms and short position in the lowest tercile of *PPR* (αPPR) firms yields a statistically and economically significant positive return of 0.41% to 1.88% (0.40% to 1.33%) over the next quarter, depending on the asset pricing model employed for risk adjustment.

Using both cross-sectional and panel regression techniques with standard control variables, we next investigate the extent to which firm-level *aPPR*s predict returns in the equity REIT market. Our baseline results suggest that quarterly lags of our *PPR* measures predict returns in the public REIT market in the subsequent quarter. We find that two-quarter, three-quarter, and four-quarter lags of *aPPR*s also predict equity REIT returns in quarter *t*. These findings suggest that the slow diffusion into stock prices of information about the performance of the local markets in which the firm is invested is at least partially explained by the information asymmetry between capital market participants and private property market investors. Our findings are consistent with Korniotis and Kumar (2013), Bernile et al. (2015), Smajlbegovic (2019), and Ling et al. (2019b). We also find that *aPPR* over the prior year predicts equity REIT returns in the following year.

Our results are robust to different measures of *PPR*, to different model specification, to using both quarterly and annual data, and to using both cross-sectional and panel regressions with property type (or firm) and time fixed effects. In addition, we conduct a battery of additional robustness tests. We "de-lever" REIT returns to remove the effects of financial leverage following Ling and Naranjo (2015) and find similar results, suggesting that changes in debt financing do not explain the predictive power of *PPR* we document. Numerous prior studies using index-level return data find that predictability runs from public markets to private markets (e.g., Riddiough, Moriarty and Yeatman 2005; Pagliari, Scherer and Monopoli, 2005; Boudry, Coulson, Kallberg and Liu, 2013; Ling and Naranjo, 2015). Therefore, we use *aPPR* as the dependent variable instead of returns and regress it on lagged firm-level REIT returns. We find no "reverse" predictability at the firm level. Lastly, we show that the slow diffusion of asset-level information into stock returns we document is not driven by the liquidity of local property markets.

We next investigate potential mechanisms that can explain the ability of our *PPR* measures to predict REIT returns. As CRE returns consist of two components, the return from rental income and price appreciation, we decompose *aPPR*s into an income return component (*aPPR_INC*) and a price appreciation component (*aPPR_PRC*). We find a significant positive link between *aPPR_PRC* and REIT returns. In contrast, the ability of *aPPR_INC* to predict returns is limited. We also find a positive and significant relationship between "same-store" rental growth and *aPPR_PRC*. This suggests that *PPR* predictability is not purely driven by changes in the property portfolio composition of REIT portfolio and that at least part of the link between *aPPR_PRC* and REIT returns is explained by rental growth.

Given that the ability of *PPR* to predict REIT returns is driven by the price appreciation component of its geographically weighted “local” NCREIF return and that a greater portion of the expected total return on property investments in major “gateway” (low cap rate) markets is expected to come from price appreciation, we decompose each firm’s time-varying *aPPR* into three components: gateway (first tier), second tier, and tertiary markets. Consistent with prior literature, we find that REIT allocations to properties in gateway markets tend to outperform their allocations to non-gateway markets (Ling et al., 2019a). More importantly, the information contained about price appreciation in gateway markets released each quarter by NCREIF better explains firm-level REIT returns than the information contained in the reported return performance of the more income-orientated secondary and tertiary markets.

There is a growing literature that examines the effects of geographic asset allocations on REIT returns. Ling et al. (2019a) find that the percentage allocations of an equity REIT’s property portfolio across metropolitan areas help explain short-run cross-sectional variation in REIT returns. Ling et al. (2020) find that the extent to which an equity REIT tilts the allocation of its asset portfolio toward properties located in its headquarters MSA (“home bias”) is associated with higher realized returns. Fisher et al. (2020) find that REITs that invest in high-density locations have higher betas and thus higher expected rates of return. Zhu and Lizieri (2019) focus on estimating a property market “beta” that captures the tendency of equity REIT returns to commove with the national NCREIF index. In contrast to these studies, we focus on the explanatory power of the “alpha” generated by a REIT’s underlying property portfolio that is not explained by sensitivities to systematic risk factors but more likely driven by local-relevant information.

This study also contributes to the extensive literature on the predictability of REIT returns (Nelling and Gyourko, 1998; Ling, Naranjo, and Ryngaert, 2000), the relation between private and public CRE returns (Riddiough, Moriarty and Yeatman 2005; Pagliari, Scherer and Monopoli, 2005; Horrigan, Case, Geltner, and Pollakowski, 2009; Boudry, Coulson, Kallberg and Liu, 2013; Yunus, Hansz and Kennedy 2012; Muhlhofer, 2013; Ling and Naranjo, 2015), as well as the effects of geographic asset allocations on REIT asset pricing (Ling, Naranjo and Scheick, 2018, 2019; Zhu and Lizieri, 2019).

The paper proceeds as follows. Section 2 describes our methodology. Section 3 describes the data. Section 4 discusses the results. Section 5 concludes.

2. Methodology

Our first task is to construct a quarterly time-series of risk-adjusted property portfolio returns, *aPPR*s, for each equity REIT in our sample. For each REIT *i* at the beginning of year *t*, we first calculate the percentage of its property portfolio, based on book values, invested in each property type in each U.S. MSA. We next match these portfolio allocations to each property type and MSA with the quarterly unlevered return on the corresponding NCREIF NPI property-type-MSA sub-indices; for example, the quarterly returns on office properties in Dallas in quarter *t*.[3] These MSA-level NCREIF NPI returns are then weighted by the percentage of the REIT's portfolio invested in each MSA. This is done separately for each quarter for each property type owned by the REIT. Thus, we estimate each REIT's unlevered property portfolio return (*PPR*) in each quarter as the average return across all MSAs where a REIT owns any property, weighted by the MSA-level total book value for each REIT. We repeat this process for each REIT in each quarter to produce an estimated time series of unlevered total returns on each REIT's underlying property portfolio.[4]

It is well known that the quarterly appreciation return calculated by NCREIF for each property in the NCREIF NPI database is not based on a transaction price unless the property happened to be sold in that quarter. Instead, the market value of the property at the end of the quarter is estimated by a third-party fee appraiser or by the owner's asset manager. These "appraisal-based" appreciation returns are thought to produce estimated price appreciation returns that are lagged and smoothed, and this smoothing understates return volatility (see, for example, Geltner, 1993, Geltner and Ling, 2007).[5]

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[3] 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. NCREIF's flagship index, the NCREIF Property Index (NPI), tracks property-level returns on a large pool of commercial real estate assets acquired in the private market for investment purposes only. 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.

[4] Although the MSA allocations based on the S&P Global data remain constant for a calendar year, the NPI returns vary each quarter.

[5] The hypothesized lagging and smoothing of appraisal-based returns and indices is generally attributed to two sources. First, although there is some debate in the literature, the use of comparable sales that sold in the past to appraise the current market value of a property is thought to impart a backward-looking bias that produces estimated price changes that lag changes in "true" (but unobservable) market values. Second, formal appraisals of constituent properties in the NCREIF NPI Index by third party appraisers are usually conducted annually; the

The potential lagging and smoothing of estimated firm-level property portfolio returns, and its effect on mean returns, standard deviations, and correlations, is a concern in time-series studies. However, our analysis is largely cross-sectional because our *PPR* measure is based on investments in each property type and MSA. In addition, we are not using NCREIF NPI market values as indicators of "true" market values, but rather as a proxy for the information an informed participant in the private market would have on the value of a REIT's CRE portfolio. In fact, the variation in the speed of information diffusion across property types and locations is what we aim to capture in the predictability of returns across firms. We also employ annual NPI returns, which substantially reduces any appraisal smoothing (see Geltner 1993).

2.1 Risk-Adjusted Property Portfolio Returns (aPPRs)

We use three steps to estimate quarterly risk-adjusted property portfolio return. In step 1, we regress firm-level monthly REIT returns on common (time-series) risk factors using rolling 60-month regressions:

$$\begin{aligned} Ret_{i,t} - r_{f,t} = \alpha_i + \beta_{i,MKT}\left(MKT_t - r_{f,t}\right) + \beta_{i,INT}\left(Treasury_t - r_{f,t}\right) + \beta_{i,Size}SMB_t \\ +\beta_{i,Value}HML_t + \beta_{i,Mom}UMD_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where

- $Ret_{i,t} - r_{f,t}$ is the total return of firm i in month t in excess of the one-month U.S. Treasury yield;
- $MKT_t - r_{f,t}$ is the return on the market portfolio in excess of the risk-free rate in month t;
- $Treasury_t - r_{f,t}$ is the yield on 10-year Treasury bonds in excess of the risk-free rate in month t;
- SMB_t *and* HML_t are standard Fama-French (1993) risk factors that capture the impact of firm size and expected firm growth on returns, respectively;
- UMD_t captures return momentum;
- $\varepsilon_{i,t}$ is a standard error term.

The slope coefficients from this regression are the estimated sensitivities of each REIT's returns to common public market asset pricing factors. The monthly time series of coefficient

property's asset manager is responsible for updating the appraisal internally in the intervening quarters. This leads to what is commonly called the "stale" appraisal problem.

estimates for $\widehat{\beta_{MKT}}$, $\widehat{\beta_{INT}}$, $\widehat{\beta_{Size}}$, $\widehat{\beta_{Value}}$, and $\widehat{\beta_{Mom}}$ for each REIT are collected for the ending month of the previous quarter for use in step 3.

In step 2, we regress quarterly firm-level returns on proxies for the quarterly return and liquidity in the private CRE market, both measured at the national level. This is to obtain the sensitivity of each REIT's returns to systematic risk factors in the private CRE market. Our proxy for the national-level private market return is the NCREIF NPI National Index; our proxy for CRE liquidity at the national level is the quarterly market value weighted turnover in the NCREIF NPI database. More specifically, we estimate the following equation for each REIT in each quarter using rolling 20-quarter windows:

$$Ret_{i,q} - r_{f,q} = \alpha_i + \beta_{i,PR}(NPI_q - r_{f,q}) + \beta_{i,TO}TURN_q + \varepsilon_{i,q} \tag{2}$$

where

- $Ret_{i,q} - r_{f,q}$ is the total return of firm i in quarter q in excess of the one-month U.S. Treasury yield over the same quarter;
- $NPI_q - r_{f,q}$ is the national level NCREIF NPI return in quarter q in excess of the one-month Treasury yield over the same quarter;
- $TURN_q$ is the total dollar value of properties in the NCREIF NPI database that sold in quarter q, divided by the market value of all properties in the database at the beginning of quarter q;
- $\varepsilon_{i,q}$ is a standard error term.

$\widehat{\beta_{i,PR}}$ and $\widehat{\beta_{i,TO}}$ are the estimated sensitivities in quarter q of each REIT's returns to proxies for private market returns and turnover at the national level. The quarterly time series of coefficient estimates for $\widehat{\beta_{i,PR}}$ and $\widehat{\beta_{i,TO}}$ for each REIT are collected for use in step 3.[6]

Finally, in step 3, for each quarter we run a cross-sectional regression with $PPR_{i,q}$ as the dependent variable and the estimated risk-factor sensitivities from equations (1) and (2) ($\widehat{\beta_{i,PR}}$, $\widehat{\beta_{i,TO}}$, $\widehat{\beta_{i,MKT}}$, $\widehat{\beta_{i,INT}}$, $\widehat{\beta_{i,Size}}$, $\widehat{\beta_{i,Value}}$, and $\widehat{\beta_{i,Mom}}$) for each REIT as the independent variables. That is, we estimate:

$$PPR_{i,q} = \gamma_q + \sum_{s=1}^{7} \lambda_{s,q}\beta_{i,s,q} + \varepsilon_{i,q} \tag{3}$$

where $\lambda_{s,q}$ is the estimated sensitivity of REIT i's property portfolio return in quarter q to the estimated loading of risk factor s. The *orthogonalized* property portfolio return for REIT i in

[6] Equations (1) and (2) can be collapsed into a single equation if quarterly data is used to obtain both public market and private market return sensitivities. Doing so yield very similar results.

quarter q, $aPPR_{i,q}$, is equal to $\gamma_q + \varepsilon_{i,q}$. This return is independent of the risk factor loadings and can be interpreted as the alpha achieved by REIT i in quarter q on its property portfolio.[7] We posit that $aPPR_{i,q}$ contains private information about local property markets, which is not immediately reflected in the firm's stock price. We compound quarterly $aPPR$s to obtain annual risk-adjusted property portfolio returns ($aPPR_{i,a}$) for each REIT.

2.3 Does Information About Local Economic Activity Predict Stock Returns?

To investigate the extent to which *aPPRs* help to explain the cross-section of REIT returns in a multivariate setting, we estimate the following model using both Fama–MacBeth cross-sectional regressions as well as panel regressions:

$$Ret_{i,q} - r_{f,q} = \alpha_q + \beta_q \alpha PPR_{i,q-1} + \mathbf{X'}_{\boldsymbol{i,q-1}}\mathbf{b_q} + PropFE + \delta_i + \theta_q + \varepsilon_{i,q} \quad (4)$$

where $Ret_{i,q} - r_{f,q}$ is the REIT return in excess of the risk-free rate in quarter q, $\alpha PPR_{i,q-1}$ is the lagged quarterly risk-adjusted property portfolio returns in quarter q-1, $\mathbf{b_q}$ is a vector of lagged firm characteristics, $PropFE$ are fixed effects that control for the property type focus of the REIT, and $\varepsilon_{i,q}$ is a standard error term. δ_i and θ_q represents a vector of firm fixed effects and time fixed effects, respectively, in a panel regression setting. If the estimated coefficient on $\alpha PPR_{i,q-1}$, β_q, is positive and significant, it indicates that information about the performance of markets in which the firm has economic interests is predictive of quarterly REIT returns, even after controlling for standard firm characteristics and systematic risk.

3. Data

The initial sample of publicly traded U.S. equity REITs is obtained from the CRSP-Ziman database. We require non-missing values for the following items for each REIT at the end of each time period: REIT identifier (PERMNO), total returns, stock price, property type and sub-property type focus, and stock market capitalization. The initial sample includes 415 unique equity REITs traded on NSYE, Amex, and Nasdaq from 1996 to 2018. Annual and quarterly accounting data are obtained from Compustat as well as the S&P Global Real Estate Properties database (formerly SNL Real Estate). Total returns on a broad-based stock market portfolio and the risk-free rate, along with Size, Value, and Momentum risk factors,

[7] We also construct a naïve *aPPR* measure by subtracting the private market returns of a REIT property portfolio at the national level from its PPRs. The rationale is to focus on the location-specific effects while controlling for the REITs' exposures to alternative property types. These results are similar and will be provided upon request.

are obtained from Ken French's website.[8] Monthly data on 10-year Treasury bond yields are downloaded from CRSP. Proxies for private market CRE returns and the data needed to construct a quarterly estimate of property turnover at the national level are obtained from NCREIF. The NCREIF Property Indices (NPI) are estimated unleveraged composite total returns for private CRE properties held for investment purposes.

To measure time-varying, firm-level allocations to each property type (sub-property type) and each MSA, we collect the following data from the S&P Global Real Estate Properties on an annual basis for each property held by a listed equity REIT during the period 1996–2018: property owner (institution name), property type, geographic (MSA) location, acquisition date, sale date, book value, initial cost and historic cost. Our analysis begins in 1996 (end of 1995) because this is the first period for which S&P Global provides historic cost and book value information at the property level. NCREIF NPI returns are only available for core property types; that is, apartment, office, industrial and retail properties. We therefore focus our analysis on REITs that own and operate these four core property types as defined by CRSP-Ziman.

Before matching with NCREIF NPI data, our REIT property-level data set contains 452,576 property-year observations for 275 unique core REITs over our 1996–2018 sample. We first calculate, for each REIT i at the end of year t, the percentage of its property portfolio, based on depreciated book values, invested in each property type in each MSA.[9] We then manually match these portfolio allocations with the quarterly total return on the corresponding NCREIF NPI property-MSA sub-indices; for example, the quarterly return on office properties in New York.[10] These MSA-level NCREIF returns are then value-weighted by the percentage of the REIT's portfolio invested in each MSA. This is done separately each

[8] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[9] The use of book value in place of true market values may understate the (value-weighted) percentage of the REIT portfolio invested in MSAs that have recently experienced a relatively high rate of price appreciation. Conversely, their use may overstate the percentage of the REIT portfolio that is invested in MSAs that have experienced relatively large price declines.

[10] The capital gain component of the quarterly total return for each property is based on the estimated (appraised) value of the property at the beginning and end of the quarter. However, if the property happens to sell in that quarter, the actual transaction price is used instead of the estimated value at the end of the quarter to determine capital appreciation. Quarterly rents, operating expenses, and capital expenditures are reported in a uniform fashion by property owners to NCREIF, which are used to determine the income component of each property's total return. The property-level returns are then aggregated into value-weighted or equally weighted return indices for various property types and geographies.

quarter for each property type owned by the REIT. This produces an estimated quarterly return on each REIT's underlying property portfolio.[11]

Finally, in each quarter, we orthogonalize *PPR* with respect to return sensitivities by running a cross-sectional regression following the procedures detailed in the previous section. This produces a time-series of firm-level *PPR*s. This step left us with 217 REITs or 8,855 firm-quarter observations. Quarterly *αPPR*s within a year are then averaged to obtained annual estimates of risk-adjusted returns on the REIT's underlying property portfolio. Our final dataset for quarterly (annual) regression analysis consists of 6,591 firm-quarter (1,754 firm-year) observations.

To control for local economic activity, we use the State Coincident Indexes (SCIs), developed by Crone and Clayton-Matthews (2005). The SCI is a state-level time-series measure of economic activity and combines four indicators, including nonfarm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and real wage and salary disbursements. Next, we follow Smajlbegovic (2019) and calculate the firm-specific regional economic activity proxy by multiplying the predicted growth rate of the SCI by the percentage of the REIT's portfolio invested in each state. This is done each quarter separately for each REIT. To mitigate the potential concern that this value-weighted quarterly index of each firm's "local" economic activity is correlated with national economic activity, we regress it on the return sensitivity to the growth rate of the national economic activity, and on the sensitivities to common risk factors (market, size, value and momentum). This produces an orthogonalized index of economic activity, IEA_q. Because of the potential correlation between local property market conditions and returns and local economic activity, we construct a third test variable, *OαPPR*, by orthogonalizing *αPPR* with respect to lagged *IEA. OαPPR* is a risk-adjusted return measure that is uncorrelated with local economic activity.

Our control variables include determinants of the cross section of REIT returns identified in the prior literature (e.g., Bond and Xue, 2017; Letdin et al., 2019). *Momentum* is defined as the firm's cumulative return over the prior year, *ILLIQ* is the natural logarithm

[11] In some cases, the needed MSA-level return index for a particular property type is not available from NCREIF. This occurs if there are less than six (we need to check this) properties of that property type in the MSA. Assume, for example, that a REIT owned an office property in Indianapolis, Indiana in the 4th quarter of 2015. However, the NCREIF NPI does not contain a return index for Indianapolis office properties in the 4th quarter of 2015. We would then substitute the return index for office properties in the state of Indiana.

of the stock's Amihud (2002) illiquidity measure,[12] *IVOL* is the idiosyncratic volatility of the firm's stock price. Using the Compustat database, we define *Size* as the logarithm of the book value of assets, *B/M* as the ratio of book equity to market equity, and *Profitability* as operating profitability, defined as annual revenues minus the cost of goods sold, interest expense, and selling, general, and administrative expenses, divided by book equity at the end of the previous fiscal year. *Investment* is defined as the quarterly (or annual) growth rate in non-cash assets, and *Leverage* is the total book value of debt divided by the book value of total assets. These firm characteristics are measured at the end of the quarter (or year) prior to when returns are measured. See Appendix 1 for variable descriptions.

4. Results

4.1 Summary Statistics

Panel A of Table 1 reports summary statistics for our quarterly data. Levered REIT returns in excess of risk-free rate averaged 2.53% with a standard deviation of 15.27%. The risk-adjusted excess return (alphas) ranges from 0.79% to 1.53%, reflecting the use of different asset pricing models. As Green Street restricts its coverage to the most actively traded REITs, the use of Green Street data reduces our sample size to 3,316 observations.

The means of *PPR* and *aPPR* are positive and highly similar (both 2.30%), as are their distributions. Orthogonalizing *aPPR* with respect to an index of local economic activity largely reduces the mean; in fact, the mean (median) of *OaPPR* is close to zero (0.090%). Despite the differences in means, when we standardize the three *PPR* variables and plot them over the 1996-2018 sample period, they share similar time-series patterns. As shown in Figure 1, after peaking in 2006Q2, our *PPR* measures sharply dropped in 2008 but quickly rebounded in late 2009.

By decomposing *aPPR* into its appreciation return (*aPPR_PRC*) and income return (*aPPR_INC*), we find that the majority of *aPPR* is generated by the income return (1.66%), not price appreciation (0.63%). Moreover, the standard deviation of the appreciation component is approximately 3.4 times its mean (=2.14/0.63), while the standard deviation of the income component is just 23 percent of its mean (=0.38/1.66). This is because rental income changes slowly and is much easier to predict than changes in capitalization rates. This finding is consistent with Ghent and Torous (2019) who conclude that the income return

[12] Amihud (2002) defines illiquidity as the daily volume price impact during year *t*.

component is similar across public and private CRE indices and exhibits little volatility, whereas the price appreciation component varies significantly across indices.

To further examine the channel(s) through which *PPR* affects future REIT returns, we obtain a measure of "same-store" NOI growth for each REIT in each quarter from the S&P Global Real Estate Properties database. This variable captures the quarterly change in NOI only for properties held by the REIT at the beginning and end of the quarter; thus, it is not contaminated by changes in the property holdings of a REIT from quarterly to quarter (Ambrose et al. 2000). Same-store NOI growth, *SS_NOI_Growth* has a mean of 2.40% and a standard deviation of 4.44%.[13] This variable is available only for a smaller sample of larger REITs.[14]

An average REIT in our sample has a quarterly book-to-market ratio of 0.67, return momentum of 12.25%, an investment rate of 3.16%, Amihud illiquidity of 1.04, idiosyncratic volatility of 1.45%, and operating profitability of 1.56%. Stock market capitalization at the end of each quarter and total leverage ratio averaged $2.8 billion and 53%, respectively. These statistics are comparable to prior studies. For completeness, we report summary statistics for our annual data in Table 1, Panel B. Importantly, the annual averages of our quarterly PPR measures and the summary statistics for our control variables are similar to those in Panel A.

4.2 Portfolio Sorts

If lagged *PPR*s predict REIT returns, investing in REITs with high *PPR*s should yield superior performance relative to a portfolio of REITs with low *PPR*s. We therefore sort REITs into *PPR* (or *αPPR*) terciles (low, medium and high) at the beginning of each quarter, rebalancing the constituents of the three portfolios at the beginning of each quarter based on each REIT's *PPR* measures in the prior quarter. We then calculate quarterly equal-weighted risk-adjusted returns for *PPR* and *αPPR*-based portfolios using various asset pricing models.

The quarterly results reported in both Panels A and B of Table 2 suggest that the relationship between lagged *PPR* measures and REIT returns increases monotonically in *PPR*. For example, the average quarterly excess return increases from 1.61% to 3.48% (1.95% to 3.28%) when moving from the lowest to the highest *PPR* (*αPPR*) portfolio. A portfolio

[13] Raw NOI Growth has a mean of 15.90% and a standard deviation of 55.47 percent.
[14] The average market capitalization of REITs with non-missing same-store NOI data is around $3.3 billion, compared to $733 million for the rest of our sample.

strategy that is long the highest and short the lowest *PPR* (*αPPR*) tercile yields a statistically and economically significant positive return of 0.41% to 1.88% (0.40% to 1.33%).[15] Results are similar when we calculate risk-adjusted returns using the CAPM, the Fama-French (1993) three-factor, and the Carhart (1997) four-factor models. The results presented in Panels C and D of Table 2 are based on annualized *PPRs*, *αPPRs*, and subsequent annual REIT returns. Overall, these univariate portfolio sorts suggest that *PPR*s are highly predictive of subsequent REIT returns.

4.3 Baseline Regression Results

To examine in a multivariate setting the extent to which property portfolio alphas (*PPRs*) explain variation in excess REIT returns (*RetRf*), we estimate equation (4) using both Fama–MacBeth annual cross-sectional regressions and panel regressions. The cross-sectional regression results are reported in Panel A of Table 3. Models (1) through (4) contain results estimated using quarterly data; models (5) through (8) present our results estimated with annual data. As a starting point, we first estimate equation (4) without our main variable of interest, *PPR*. The results are reported as model (1). Similar to the results in other studies (e.g., Bond and Xue, 2017; Letdin et al., 2019), we find that return momentum and lagged profitability are positively and significantly associated with subsequent REIT return, while idiosyncratic stock price volatility is negatively related to total returns.

In model (2), raw *PPR* is added as an explanatory variable. The estimated coefficient on *PPR* is positive and significant at the 1% level. A change in *PPR* from the bottom to the top quartile is associated with an economically meaningful increase in quarterly *RetRf* of 1.06 percentage points, or a 42% increase relative to its mean (2.53%). In model (3), we replace *PPR* with *αPPR*. The estimated coefficient on *αPPR* is also positive and highly significant: a change in *αPPR* from the bottom to the top quartile is associated with a 0.85 percentage point increase in quarterly *RetRf*.

In model (4), we replace *αPPR* with *OαPPR*, which is the residual from a regression of *αPPR* against our firm-level, weighted average measure of state-wide economic activity (*IEA*). The estimated coefficient on *OαPPR* is again positive, statistically significant, as well as economically significant: a change in *OαPPR* from the bottom to the top quartile is associated with a 0.617 percentage point increase in *RetRf*, or a 34% increase relative to its mean.

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[15] Similar evidence is found for value-weighted portfolio return.

In models (1) through (4), the estimated coefficients on *Momentum* and *Profitability* are positive and significant, while the estimated coefficient on *IVOL* is weakly negative. The estimated coefficients on *IEA* cannot be distinguished from zero, which indicates that REIT returns are not related to the time-varying regional economic activity to which the firm is exposed that is uncorrelated with systematic risk factors and nationwide economic growth.

Models (5) through (8) show results using annual data. The estimated coefficients on our three measures of *PPR* remain positive and significant at the 5% level. A change in *αPPR* from the bottom to the top quartile is associated with a 2.10 percentage point increase in returns over the next year. Interestingly, the estimated coefficients on *IEA* is negative and significant in models (6) through (8), suggesting that increases over the past year in the regional economic activity to which the firm is exposed are negatively related to REIT returns in the subsequent year.

In Panel B of Table 3, we report the results from estimating equation (4) using panel regressions. Both firm and (quarter or annual) time fixed effects are included. The estimated coefficients on our three measures of PPR remain positive and significant in all specifications. Taken together, the results displayed in Table 3 provide strong evidence that the estimated returns earned on an equity REIT's underlying property portfolio are predictive of future stock returns.

In Table 4, we further investigate the persistence and speed at which the information contained in *PPR* is absorbed in stock prices. Control variables are the same as in Table 3 and are suppressed for brevity. The results reported as model (1) reproduce, for comparison, the results for model (3) in Panel A, Table 3 in which *αPPR* is lagged one quarter. In models (2) through (5) we lag *αPPR* two quarters, three quarters, four quarters, and five quarters, respectively. For lags up to five quarters, the estimated coefficient on *αPPR* remains positive and significant, although at a slightly reduced significance level relative to a one-quarter lag. Nevertheless, we find in untabulated results that two- and three-month lags of *αPPR* provide the majority of the explanatory power.

4.4 Robustness Tests

Our findings thus far suggest that risk-adjusted property portfolio returns predict the cross-section of returns in the public REIT market, suggesting a slow diffusion of asset-level information into stock returns. However, increases in *PPR* might lead to higher leverage and risk at the REIT level because of increased debt capacity. The MSA-level NCREIF NPI return indices we use to calculate PPRs represent unlevered returns, which may therefore distort the prediction of levered REIT returns.

To investigate this issue, we "unlever" firm-level REIT returns to remove the effects of financial leverage following the procedure employed by Ling and Naranjo (2015).[16] As shown by the results reported in Table 5, the estimated coefficients on *aPPR* and *OaPPR* remain positive and significant. This suggests that increases in debt financing that result from price appreciation in the REIT's underlying property portfolio do not drive the ability of *PPR* to predict REIT returns.

Prior studies using *index*-level (aggregate) return data conclude that predictability runs *from public to private* markets. i.e., public REIT returns predict private commercial real estate returns at the index level. In sharp contrast, using *firm*-level data, we find that equity REIT returns can be predicted with the returns on the REIT's underlying property portfolio; that is, predictability runs *from the private market to the public market*. To formally test for reverse causality, we use *aPPR* as the dependent variable in equation (4) and regress it on lagged firm-level REIT returns as well as our control variables. The results displayed in Appendix 2 clearly reveal no ability of lagged REIT returns to predict *aPPR*; more specifically, the estimated coefficients of equity returns, both contemporaneous and lagged one to four quarters, are statistically insignificant in all model specifications.

We further explore whether the return predictability of *aPPR* is driven by a subsample of firms or time periods. Asset allocation decisions by larger firms or constituents of the S&P 500 index might enjoy larger visibility among investors. In addition, institutional investors may benefit from superior private information about local markets because they are more efficient monitors. In Appendix 3, we augment Equation (4) by interacting *aPPR* with various firm characteristics, including firm size, a dummy variable that indicates the firm is a S&P 500 constituent, and the percent of shares owned by institutional investors. We also include a dummy variable to control for the Great Recession (2017Q1 – 2019Q2, as defined by NBER). These interaction coefficients are insignificant.

[16] The unlevered REIT return is defined as the unlevered return on assets (or weighted average cost of capital). Specifically, it is calculated as the weighted average of (1) levered total return on equity, (2) the total return earned by the firm's long-term and short-term debt holders, and (3) the return earned by preferred shareholders. The three components are weighted by equity, debt and preferred shares in the firm's capital structure, respectively.

4.5 The Impact of Liquidity

Our results strongly suggest that the return performance of the markets in which a REIT's underlying property portfolio is located is predictive of subsequent REIT returns. This finding, in turn, suggests that the effects of changes in a firm's *PPR* are persistent because information about the market value of the REIT's property portfolio is diffused slowly and not immediately capitalized by the marginal investor into the REIT's stock price. However, it has been documented that the liquidity and expected returns of financial assets are negatively correlated (e.g., Amihud, 2002, Pástor and Stambaugh, 2003, Acharya and Pedersen, 2005). Similar evidence has been found for REITs (e.g., Brounen et al., 2007; Hoesli et al., 2017). Importantly, Bond and Chang (2012) and Agarwal and Hu (2014) establish a significant correlation in liquidity between the public market and the private market. In a recent study, Wang et al. (2018) find that cross-learning about peer firms' underlying assets helps to explain liquidity commonality among REITs. Downs and Zhu (2019) show that local property market liquidity influences the liquidity of publicly traded REITs. Given these findings, it is possible that the ability of *aPPR* to predict REIT returns that we document is driven, at least in part, by the correlation of *aPPR* with liquidity in the private market.

To investigate this issue, we follow Downs and Zhu (2019) and construct a time-varying measure of each REIT's exposure to local real estate liquidity. More specifically, for each firm-quarter, we calculate a weighted average of the turnover in each market in which the REIT owns properties. The weights are each firm's (non-zero) portfolio allocation in each MSA. Quarterly turnover in each MSA is calculated as the transaction value (in dollar terms) of all properties sold from the NCREIF NPI index in a quarter divided by the total market value of all properties in the NCREIF NPI database in that MSA at the beginning of the quarter.[17]

In column (1) of Table 6, we display our baseline results (see model (3) of Panel A, Table 3) for comparative purposes. In column (2), we report results from regressing REIT returns on our geographically weighted turnover measure for the private market, lagged one quarter (*PropTO*). In Column (3), we report results from estimating our REIT return regression using both *aPPR* and *PropTO* as explanatory variables. While the estimated coefficient on *aPPR* remains positive and highly significant, the estimated coefficient on *PropTO* cannot be distinguished from zero in either model. The corresponding results using

[17] If turnover is not available for a MSA in a quarter, we use NCREIF NPI turnover at the state level.

annual regressions are reported in columns (4) through (6). Again, we find no evidence that private market liquidity (turnover) predicts REIT returns.

To check for nonlinearities, we also create dummy variables for values of *PropTO* above the median, above the 75th percentile, and above the 90th percentile value of *PropTO*. In untabulated regressions, we separately interact these dichotomous measures of turnover with *aPPR*. None of the estimated coefficients on the interaction terms are significant, suggesting that the slow diffusion of asset-level information into stock returns is not driven by the liquidity of local property markets.

4.6 Potential Mechanisms that Drives the Predictability of Returns using aPPRs

We next examine the channel(s) through which *PPR*s predict subsequent REIT returns. CRE returns consist of two components: the return from net rental income (net operating income, NOI) and the return from price appreciation. We therefore decompose *aPPR* into an income return component (*aPPR_INC*) and a price appreciation component (*aPPR_PRC*). Our quarterly summary statistics in panel A of Table 1 indicate that the income component represents a significant fraction of *aPPR*; on average, 74% (=1.68%/2.26%) of *aPPR* is derived from *aPPR_INC*. Moreover, due to the existence of in-place, often long-term, leases and the wide availability of information on competitive rental rates and terms, the income generated by a REIT's property portfolio over the next quarter or year can be estimated relatively more accurately by interested parties than future price appreciation.

However, property prices are highly sensitive to unanticipated changes in cap rates and rents. As revealed in Table1, the standard deviation of *aPPR_PRC* is 3.4 times its mean. In contrast, the standard deviation of *aPPR_INC* is just 23% of its mean. In addition, the information available on cap rates and market values is restricted by the infrequency with which comparable properties sell. This lack of comparable sale transactions slows the diffusion of information on price changes in a local market.

To investigate whether the return predictability we document is attributable to variation in price appreciation or the income return generated by in-place NOI, we re-run our baseline regressions with *aPPR* decomposed into its income and price appreciation components. The results reported in Table 7 are consistent with the price appreciation story. All the coefficient estimates on *aPPR_PRC* are positive and highly significant. The economic significance is almost as large as *aPPR* itself. For example, a change in *aPPR_PRC* from the bottom to the top quartile is associated with an increase in quarterly *RetRf* of 0.76 percentage points. In contrast, none of the estimated coefficients on *aPPR_INC* are statistically significant. Similar results are obtained using both quarterly data (columns (1)-(3)) and annual data (columns (4)-(6)). We also find similar results for *aPPR_PRC* using panel regressions (results untabulated).

Next, we replace our dependent variable with same-store NOI growth. There are two advantages of using the same-store NOI growth. First, it allows us to pin down whether the ability of the price appreciation component of *PPR* to predict REIT returns is purely driven by changes in cap rate or by a combination of cap rate changes and changes in rental income. In other words, *PPR* should have no ability to predict a REIT's same-store NOI growth if the results are entirely driven by changes in cap rate. Although the relations between each component and *PPR* are not mutually exclusive, it is important to understand whether one link dominates the other.

Second, as firms acquire and dispose of properties in different markets with different levels of information asymmetry, the ability of *PPR* to help predict the cross-section of REIT returns could be driven by changes in the composition of market base. If the *PPR* predictability is purely driven by changes in the local market composition of a REIT's portfolio, we should find no effect by looking at the same-store measure holding asset location constant. Finding predictability using same-store NOI growth ensures that our results are not contaminated by new acquisitions.

The results reported in Table 8 confirm a positive and significant relationship between *PPR*s and same-store NOI growth using both quarterly and annual data. Importantly, only the price appreciation component (*aPPR_PRC*) predicts same-store NOI growth. These results suggest that (1) *PPR*'s ability to predict REIT returns is not driven by changes in the property composition of REIT portfolios and (2) at least part of the ability of *PPR_PRC* to predict REIT returns is attributable to rental growth projections.

4.7 Do Asset Allocations Across Market Tiers Explain REIT Returns?

We next investigate whether the ability of *aPPR* to predict stock returns varies with the size, importance, and perceived riskiness of the markets in which the REIT is invested. Major "gateway" MSAs are thought to have investment advantages over the remaining 300-plus MSAs, including increased liquidity and information revelation due to the size and depth of these markets and the amount of market research directed at them. Of course, these perceived advantages are reflected, partially if not fully, in lower capitalization rates (higher growth expectations). In contrast, many secondary and tertiary markets are thought to be less liquid and more informationally opaque, and therefore riskier, than gateway markets. These characteristics produce higher cap rates (lower growth expectations) than those observed in gateway markets and could affect the speed at which new information about these markets is diffused to REIT investors. Therefore, one might expect that the ability of *aPPR* to predict stock returns is driven primarily by a firm's investments in secondary and tertiary markets because less information is available about the performance of these markets prior to the release each quarter of the disaggregated NCREIF return indices.

However, because capitalization rates in gateway and other "first tier" markets are lower than cap rates in secondary and tertiary markets (e.g., Beracha et al., 2017), a larger portion of the total return in gateway markets is expected to come from future rental growth and price appreciation than in secondary and tertiary markets. And future price appreciation is more difficult to forecast than net operating income over the next several quarters. Therefore, the information about price appreciation in gateway markets reported by NCREIF each quarter is more informative to REIT investors than the information contained in the reported return performance of the more income-orientated tertiary markets. This suggests that the *aPPR*s associated with allocations to gateway markets are more predictive of REIT returns than the *aPPR*s produced by allocations to secondary and tertiary markets.

To investigate this empirical issue, we divide the 362 U.S. metropolitan areas in which a REIT could potentially invest into three categories: (1) gateway markets; (2) secondary markets; and (3) tertiary markets.[18] Industry professionals have long defined the following six metropolitan areas as "gateway" markets: Boston, Chicago, Los Angeles, New York, San Francisco, and Washington, D.C.[19] We include the same six markets in our definition of gateway markets. To identify our set of secondary markets, we first identify the 25 U.S. MSAs with the largest populations based on the 2010 U.S. Census reports (Ling et al., 2019). In addition to the six gateway markets, these MSAs include the following 19 MSAs: Atlanta,

[18] 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.

[19] See, for example, Pai and Geltner (2007) and Geltner et.al. (2014).

Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Miami, Minneapolis, Orlando, Philadelphia, Phoenix, Portland, Sacramento, Saint Louis, San Antonio, San Diego, Seattle, and Tampa. All non-gateway and non-secondary MSAs are classified as tertiary markets.[20]

Using the S&P Global Real Estate Properties database, we assign each property held by each REIT in our sample to one of our three MSA categories. This classification is performed for each REIT at the beginning of year. The percentage allocation of each REIT to one of the three categories is based on the book value of each property at the beginning of the year. To illustrate the time-series variation in allocations to these three market tiers, we take the simple average of these allocations to generate a quarterly time series of average allocations to each tier. These average quarterly allocations are plotted in Figure 2. At the beginning of 1996, allocations to gateway market averaged 24%. The corresponding averages for secondary and tertiary markets we 30% and 46%, respectively. The mean allocation to gateway markets trended up over our sample period and averaged 29%. The mean allocation to tertiary markets trended down but still averaged 39%. Allocations to secondary markets remained relatively stable. The figure clearly displays the relatively large allocations many equity REITs have to tertiary markets.

Table 9 contains the firm-level statistics (means, standard deviations, and 25th, 50th, and 75th percentiles) of raw *PPR* returns and *aPPR*s for our sample. Quarterly *PPR* returns on portfolio allocations to gateway markets averaged 2.53%. The corresponding return percentages for secondary and tertiary markets are 2.23% and 2.18%; respectively. The contemporaneous time-series correlations of average *aPPR*s for gateway allocations with *aPPR*s for secondary and tertiary portfolio allocations are 0.693 and 0.655, respectively. Although gateway allocations outperformed, on average, non-gateway allocations on a raw return basis, the standard deviation of returns to gateway allocations exceeded those for both secondary and tertiary markets.

In Table 10 we report results obtained from re-estimating our baseline cross-sectional regressions (equation (4)) using, in turn, *aPPR*s for each REIT's gateway, secondary, and tertiary allocations. As a reference, the results from our baseline cross-sectional regressions

[20] Although most of the listed equity REITs in our sample hold high quality ("Class A") properties in major metropolitan areas, there is variation over time and across REITs in portfolio allocations to first tier, second tier, and tertiary markets. For example, the portfolio holdings of Boston Properties (ticker: BXP) are located almost exclusively in Boston, which is considered to be a first tier ("gateway") market. In contrast, 42 percent of the properties owned by Tanger Factory Outlet Centers, Inc. (ticker: SKT) at the end of 2017 were located in the Savannah, GA MSA. Such relatively small metropolitan areas are generally thought to be less informationally efficient than major (first tier) markets. (Ling et al., 2019; Wang and Zhou, 2020).

are reported in column (1). In models (2)-(4), we observe a decline in the extent to which private market returns predict REIT returns as we move from gateway allocations to secondary and tertiary allocations: the estimated coefficient on *aPPR*s for each REIT's gateway, secondary, and tertiary allocations is positive and significant at the 1%, 5%, and 10% level, respectively. In model (5) we include all three α*PPR*s. The estimated coefficient on *aPPR* for gateway allocations remains positive and highly significant. The estimated coefficient on *aPPR* for secondary market allocations remains positive and significant at the 10% level. However, the estimated coefficient on *aPPR* for tertiary allocations cannot be distinguished from zero.

Overall, these results suggest that the disaggregated return information released by NCREIF each quarter for tertiary markets provide less explanatory power than the return information released for allocations to gateway markets. This result is consistent with our findings that the return predictability associated with *aPPR* is attributable to cross-sectional variation in the diffusion of information about local property price appreciation, not variation in income returns (section 4.6).

5. Conclusions

In this paper, we construct a novel time-series measure of quarterly and annual property portfolio returns ("*PPRs*") for each equity REIT. Using univariate portfolio sorts, cross-sectional regressions, and panel regressions, we find that firm-level *PPR*s consistently predict returns in the equity REIT market. Our results are robust to different measures of *PPR*, to different model specifications, to using both quarterly and annual data, and to using both cross-sectional and panel regressions with property type (or firm) and time fixed effects. In addition, we conduct a battery of robustness tests. We "de-lever" REIT returns to remove the effects of financial leverage and find similar results. Because numerous prior studies using index-level return data find that predictability runs from public markets to private markets, we switch the dependent variable to be *aPPR* and regress it on lagged firm-level REIT returns. We find that "reverse" predictability does not exist at the firm level and confirm that predictability runs from the private market to the public market using firm-level data. Lastly, we conclude that local market liquidity does not drive our results.

To examine the potential mechanisms that drive the predictability of returns, we decompose *aPPR*s into an income return component and a stock price appreciation component. We find a significant positive link between the disaggregated price appreciation reported by NCREIF but no evidence that income returns predict stock returns. We also find evidence of a positive and significant relationship between "same-store" rental growth and REIT return using both quarterly and annual data. This suggests that *PPR* predictability is not driven purely by changes in the property portfolio composition of REIT portfolio. By decomposing *aPPR*s into different market tiers, we find that the disaggregated return information released by NCREIF each quarter for gateway markets provides more explanatory power than the return information released for allocations to tertiary markets.

Taken together, our results highlight the importance of understanding the extent to which "local" information about the productivity of a firm's assets is capitalized into stock prices and the speed at which it is capitalized. Our study contributes to the literature on the predictability of REIT returns and the relation between private and public CRE returns using *firm*-level, instead of *index* level, returns.

References

Addoum, Jawad M., Alok Kumar, and Kelvin Law. 2017. "Slow Diffusion of State-Level Information and Return Predictability." *Working Paper*.

Agarwal, Sumit, and Maggie Rong Hu. 2014. "Liquidity Dynamics between REIT and Property Markets." *Working Paper*.

Ambrose, Brent W., Steven R. Ehrlich, William T. Hughes, and Susan M. Wachter. 2000. "REIT Economies of Scale: Fact or Fiction?" *Journal of Real Estate Finance and Economics* 20 (2): 211–224.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5 (1): 31–56.

Acharya, Viral V., and Lasse Heje Pedersen. 2005. "Asset pricing with liquidity risk." *Journal of Financial Economics* 77(2): 375–410.

Beracha, Eli, David H. Downs, and Greg MacKinnon. 2017. "Are High-Cap-Rate Properties Better Investments?" *Journal of Portfolio Management* 43(6): 162–178.

Bernile, Gennaro, Alok Kumar, and Johan Sulaeman. 2015. "Home Away from Home: Geography of Information and Local Investors." *Review of Financial Studies* 28 (7): 2009–2049.

Bond, Shaun, and Qingqing Chang. 2012. "Liquidity dynamics across public and private markets." *Journal of International Money and Finance* 31(7): 1890– 1910.

Bond, Shaun, and Chen Xue. 2017. "The Cross Section of Expected Real Estate Returns: Insights from Investment-Based Asset Pricing." *Journal of Real Estate Finance and Economics* 54: 403–428.

Boudry, Walter I., N. Edward Coulson, Jarl G. Kallberg, and Crocker H. Liu. 2013. "On Indexing Commercial Real Estate Properties and Portfolios." *Journal of Real Estate Finance and Economics* 47 (4): 617–639.

Brounen, Dirk, Piet Eichholtz, and David C. Ling. 2007. "Trading Intensity and Real Estate Performance." *Journal of Real Estate Finance and Economics* 35: 449–474.

Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance* 52 (1): 57–82.

Crone, Theodore M., and Alan Clayton-Matthews. 2005. "Consistent Economic Indexes for the 50 States." *Review of Economics and Statistics* 87: 593–603.

Downs, David, and Bing Zhu. 2019. "REITs, Underlying Property Markets and Liquidity: A Firm Level Analysis." *Working Paper.*

Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1): 3–56.

Fisher, Gregg, Eva Steiner, Sheridan Titman, and Ashvin Viswanathan. 2020. "How Does Property Location Influence Investment Risk and Return." *Working Paper.*

Garcia, Diego, and Øyvind Norli. 2012. "Geographic Dispersion and Stock Returns." *Journal of Financial Economics* 106 (3): 547–565.

Geltner, David. 1993. "Estimating Market Values from Appraised Values Without Assuming an Efficient Market." *Journal of Real Estate Reseach* 8 (3): 325–345.

Geltner, David, and David C. Ling. 2007. "Indices for Investment Benchmarking and Return Performance Analysis in Private Real Estate." *International Real Estate Review* 10 (1): 93–118.

Geltner, David, N. Miller, J, Clayton and P.M.A. Eichholtz. 2014. *Commercial Real Estate Analysis and Investments* (3rd ed.). Mason, OH: OnCourse Learning.

Ghent, Andra C., Walter N. Torous, and Rossen I. Valkanov. 2019. "Commercial Real Estate as an Asset Class." *Annual Review of Financial Economics* 11: 153–171.

Hoesli, Martin, Anjeza Kadilli, and Kustrim Reka. 2017. "Commonality in Liquidity and Real Estate Securities." *Journal of Real Estate Finance and Economics* 55: 65–105.

Horrigan, Holly, Brad Case, David Geltner, and Henry Pollakowski. 2009. REIT-Based Property Return Indices: A New Way to Track and Trade Commercial Real Estate. Journal of Portfolio Management 35 (5): 80-91.

Korniotis, George M., and Alok Kumar. 2013. "State-Level Business Cycles and Local Return Predictability." *Journal of Finance* 68 (3): 1037–1096.

Letdin, Mariya, Corbitt Stace Sirmans, G. Stacy Sirmans, and Emily N. Zietz. 2019. "Explaining REIT Returns." *Journal of Real Estate Literature* 27 (1): 1–25.

Ling, David C., and Andy Naranjo. 2015. "Returns and Information Transmission Dynamics in Public and Private Real Estate Markets." *Real Estate Economics* 43 (1): 163–208.

Ling, David C., Andy Naranjo, and Michael D. Ryngaert. 2000. "The Predictability of Equity REIT Returns: Time Variation and Economic Significance." *Journal of Real Estate Finance and Economics* 20 (2): 117–136.

Ling, David C., Andy Naranjo, and Benjamin Scheick. 2019a. "Asset Location, Timing Ability, and the Cross-Section of Commercial Real Estate Returns." *Real Estate Economics* 47 (1): 263–313.

Ling, David C., Chongyu Wang, and Tingyu Zhou. 2019b. "The Geography of Real Property Information and Investment: Firm Location, Asset Location, and Institutional Ownership." *Real Estate Economics*.

Ling, David C, Andy Naranjo, and Benjamin Scheick. 2020. "There's No Place like Home: Local Asset Concentrations and Information Asymmetries." *Working Paper*.

Mühlhofer, Tobias. 2013. "Why Do REIT Returns Poorly Reflect Property Returns? Unrealizable Appreciation Gains Due to Trading Constraints as the Solution to the Short-Term Disparity." *Real Estate Economics* 41 (4): 814–857.

Nelling, Edward, and Joseph Gyourko. 1998. "The Predictability of Equity REIT Returns." *Journal of Real Estate Reseach* 16 (3): 251–268.

Pagliari, Joseph L., Kevin A. Scherer, and Richard T. Monopoli. 2005. "Public versus Private Real Estate Equities: A More Refined, Long-Term Comparison." *Real Estate Economics* 33 (1): 147–187.

Pai, Arvind, and David, Geltner. 2007. "Stocks Are from Mars, Real Estate Is from Venus." *Journal of Portfolio Management* 33(5): 134-144.

Pástor, Ľuboš, and Robert F. Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy* 111(3): 642–685.

Pirinsky, Christo, and Qinghai Wang. 2006. "Does Corporate Headquarters Location Matter for Stock Returns?" *Journal of Finance* 61 (4): 1991–2015.

Riddiough, Timothy J, Mark Moriarty, and P J Yeatman. 2005. "Privately Versus Publicly Held Asset Investment Performance." *Real Estate Economics* 33 (1): 121–46.

Smajlbegovic, Esad. 2019. "Regional Economic Activity and Stock Returns." *Journal of Financial and Quantitative Analysis* 54 (3): 1051–1082.

Wang, Chongyu, Jeffrey P. Cohen, and John L. Glascock. 2018. "Geographically Overlapping Real Estate Assets, Liquidity Spillovers, and Liquidity Multiplier Effects." *Working Paper*.

Wang, Chongyu, and Tingyu Zhou. 2020. "Trade-offs between Asset Location and Proximity to Home: Evidence from REIT Property Sell-offs." *Journal of Real Estate Finance and Economics*.

Yunus, Nafeesa, J. Andrew Hansz, and Paul J. Kennedy. 2012. "Dynamic Interactions Between Private and Public Real Estate Markets: Some International Evidence." *Journal of Real Estate Finance and Economics* 45 (4): 1021–1040.

Zhu, Bing, and Colin Lizieri. 2019. "Location Risk and REIT Returns Location Risk and REIT Returns." *Working Paper*, 1–42.

Figure 1: Comparison of Standardized Property Portfolio Returns

This figure shows the time-series trends in the equal-weighted property portfolio return measures, *PPR* (denoted as PPR(EW)), *aPPR* (denoted as PPR Alpha (EW)), and *OaPPR* (denoted as Orthg PPR Alpha (EW)), for the period from 1996Q1 through 2018Q4. All variables are standardized to have mean of 0 and standard deviation of 1. See Appendix 1 for variable descriptions.

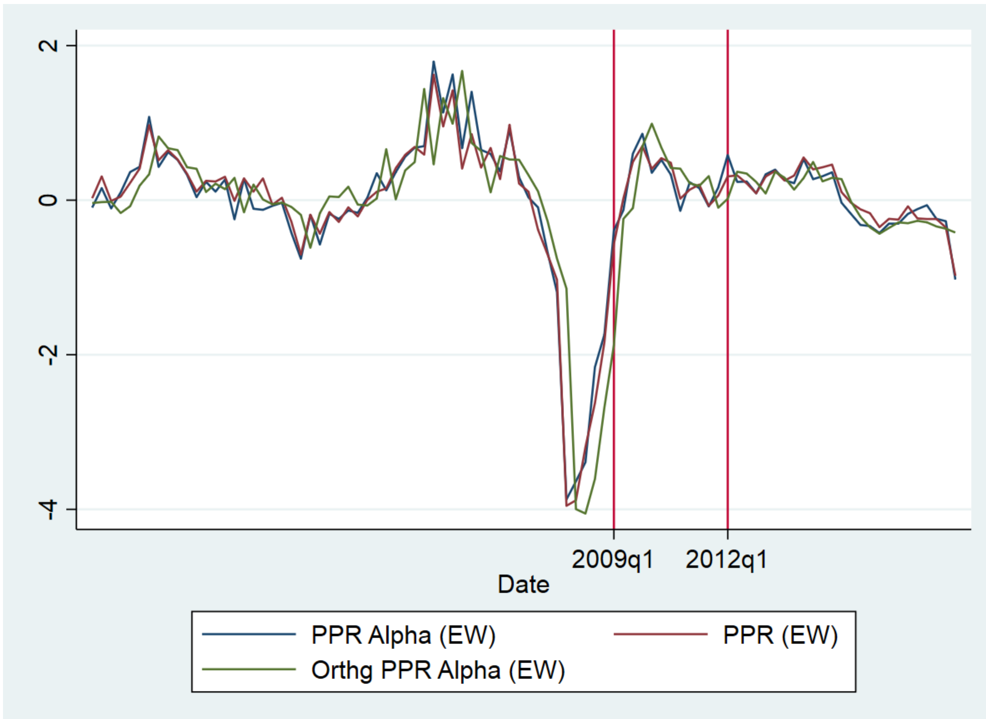

Figure 2: Gateway, secondary, and tertiary market allocations by equity REITs.

This figure shows the time-series trends in the geographic allocations by REITs across different market tiers. Allocations are displayed for (1) six gateway markets, defined as Boston, Chicago, Los Angeles, New York, San Francisco and Washington, D.C., (2) nineteen secondary markets, defined as Atlanta, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Miami, Minneapolis, Orlando, Philadelphia, Phoenix, Portland, Sacramento, St. Louis, San Antonio, San Diego, Seattle, and Tampa, and (3) tertiary markets, defined as MSAs that are neither gateway nor secondary markets. REIT market allocations are calculated using the reported adjusted cost of each core property held by REITs across MSAs within each market tier.

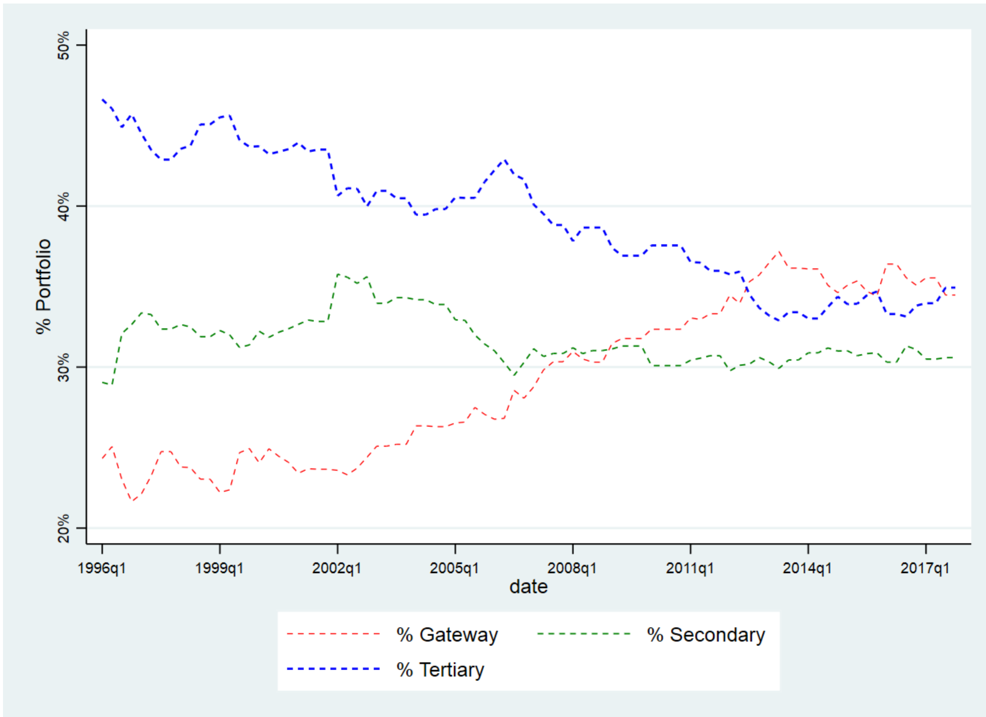

Table 1: Summary Statistics

This table shows summary statistics (number of observations, mean, standard deviation (SD), and 25th, 50th, and 75th percentiles) for a sample of 1,754 firm-year (6,591 firm-quarter) observations from 1996-2018. The statistics of the quarterly (annual) sample are shown in Panel A (Panel B). See Appendix 1 for variable descriptions.

Panel A: Quarterly Sample

	# Obs.	Mean	SD	P25	P50	P75
REIT Returns						
RetRf (Qtr)	6,591	2.53	15.27	-4.56	2.60	9.60
CAPM Alpha	6,591	1.53	2.83	0.00	1.51	3.09
FF3 Alpha	6,591	0.92	2.68	-0.41	1.02	2.41
Carhart4 Alpha	6,591	0.79	2.63	-0.58	0.88	2.34
UnlevRet (Qtr)	5,882	2.37	6.22	-1.00	2.57	6.03
GSQ (Qtr)	3,316	0.99	0.09	0.94	0.99	1.05
Property Portfolio Returns						
PPR	6,591	2.30	2.21	1.68	2.52	3.29
aPPR	6,591	2.30	2.18	1.70	2.49	3.25
OaPPR	6,591	0.00	1.00	-0.28	0.09	0.44
Channels						
aPPR PRC	6,591	0.63	2.14	0.05	0.77	1.62
aPPR INC	6,591	1.66	0.38	1.36	1.63	2.01
SS NOI Growth	3,870	2.40	4.44	-0.10	2.90	5.00
Control Variables						
IEA	6,591	1.36	0.96	1.14	1.52	1.88
Size	6,591	2786	5079	439	1176	2860
B/M	6,591	0.67	0.56	0.42	0.59	0.79
Momentum	6,591	12.25	27.62	-1.38	12.91	26.19
Leverage	6,591	0.53	0.15	0.44	0.52	0.62
Profitability	6,591	1.56	8.01	0.45	1.56	2.71
Investment	6,591	3.16	13.13	-0.49	0.86	3.62
ILLIQ	6,591	1.04	24.21	0.00	0.00	0.01
IVOL	6,591	1.45	1.18	0.93	1.14	1.52

Panel B: Annual Sample

	# Obs	Mean	SD	P25	P50	P75
REIT Returns						
RetRf (Ann)	1,754	9.76	29.12	-5.80	9.96	26.62
CAPM Alpha	1,754	6.37	11.76	-0.17	5.91	12.22
FF3 Alpha	1,754	3.97	10.65	-1.31	3.97	9.31
Carhart4 Alpha	1,754	3.48	10.39	-2.01	3.41	8.94
UnlevRet (Ann)	1,594	9.70	12.68	2.42	9.99	17.84
GSQ (Dec)	941	0.99	0.10	0.92	0.99	1.05
Property Portfolio Returns						
PPR	1,754	2.26	1.86	1.74	2.55	3.13
aPPR	1,754	2.32	1.85	1.79	2.63	3.20
OaPPR	1,754	0.00	1.00	-0.29	0.17	0.47
Channels						
aPPR PRC	1,754	0.65	1.81	0.19	0.86	1.60
aPPR INC	1,754	1.68	0.38	1.37	1.63	2.03
SS NOI Growth	1,012	2.41	4.43	0.00	2.90	4.96
Control Variables						
IEA	1,754	1.38	0.91	1.19	1.48	1.91
Size	1,754	2734	5013	436	1172	2833
B/M	1,754	0.67	0.44	0.44	0.61	0.80
Momentum	1,754	12.13	29.91	-1.62	12.20	25.72
Leverage	1,754	0.50	0.14	0.43	0.50	0.59
Profitability	1,754	5.66	25.36	1.83	5.98	9.79
Investment	1,754	15.54	33.26	-0.08	6.74	20.81
ILLIQ	1,754	0.10	0.44	0.00	0.00	0.01
IVOL	1,754	1.44	0.93	0.97	1.16	1.51

Table 2: Sorts on Property Portfolio Returns

This table shows average REIT returns for sorts on quarterly *PPR* (Panel A), quarterly *aPPR* (Panel B), annual *PPR* (Panel C), and annual *aPPR* (Panel C) for a sample of 6,591 firm-quarter (or 1,754 firm-year) observations from 1996-2018. REITs are sorted into terciles based on lagged *PPR* (or *aPPR*). The quarterly REIT returns are calculated using the chain-linked monthly excess returns or risk-adjusted returns on the market factor model, the Fama-French (1993) factor model, or the Carhart (1997) factor model. The annual *PPR* and *aPPR* are measured by the average of quarterly values during year *t*. Column "(3)-(1)" compares the average return on the portfolio of REITs between the highest and lowest tercile. Column "t-stat" ("z-stat") shows t-statistics (z-statistics) for mean (median) differences. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. See Appendix 1 for variable descriptions.

	(1)		(2)		(3)		(3)-(1)	t-stat	z-stat
Panel A: Quarterly *PPR*									
RetRf	1.61	(1.59)	2.51	(2.57)	3.48	(3.54)	1.88	4.14***	5.38***
CAPM Alpha	1.37	(1.25)	1.45	(1.49)	1.78	(1.81)	0.41	4.75***	6.01***
FF3 Alpha	0.77	(0.81)	0.80	(0.90)	1.20	(1.33)	0.43	5.38***	6.75***
Carhart4 Alpha	0.64	(0.67)	0.66	(0.75)	1.08	(1.18)	0.44	5.52***	6.61***
Panel B: Quarterly *aPPR*									
RetRf	1.95	(1.99)	2.35	(2.51)	3.28	(3.33)	1.33	2.83***	4.00***
CAPM Alpha	1.34	(1.32)	1.52	(1.47)	1.75	(1.74)	0.41	4.66***	5.08***
FF3 Alpha	0.73	(0.84)	0.89	(0.92)	1.13	(1.29)	0.40	4.89***	5.82***
Carhart4 Alpha	0.61	(0.73)	0.75	(0.77)	1.03	(1.11)	0.42	5.16***	5.59***
Panel C: Annual *PPR*									
RetRf	6.24	(7.58)	10.97	(9.21)	11.80	(12.83)	5.56	3.55***	4.00***
CAPM Alpha	5.43	(4.97)	6.07	(5.38)	7.63	(7.41)	2.20	3.24***	3.76***
FF3 Alpha	3.13	(3.08)	3.52	(3.35)	5.28	(5.69)	2.15	3.60***	4.59***
Carhart4 Alpha	2.70	(2.53)	2.92	(2.68)	4.83	(4.50)	2.13	3.62***	4.02***
Panel D: Annual *aPPR*									
RetRf	7.25	(7.51)	10.44	(10.43)	11.30	(11.82)	4.06	2.50**	3.13***
CAPM Alpha	5.04	(4.47)	6.17	(5.58)	7.92	(7.39)	2.88	4.04***	4.62***
FF3 Alpha	2.69	(2.42)	3.80	(3.89)	5.45	(5.76)	2.76	4.32***	5.45***
Carhart4 Alpha	2.34	(2.25)	3.03	(2.97)	5.08	(4.76)	2.73	4.33***	4.74***

Table 3: Regression Results of Excess Returns on Property Portfolio Returns

This table shows the regression results on the relationship between REIT excess returns and property portfolio returns. Results based on Fama-MacBeth (1973) and panel regression analysis are presented in Panels A and B, respectively. Results in Columns (1)-(4) ((5)-(8)) are based on quarterly (annual) sample of 6,591 firm-quarter (1,754 firm-year) observations from 1996-2018. The dependent variable, *RetRf*, is the chain-linked monthly stock returns of firm *i* in period *t* in excess of the rate of return of 30-day Treasury bills. *PPR* is the raw property portfolio returns of firm *i* in period *t*. *aPPR* is the residual from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities. *OaPPR* is the residual from a regression of *aPPR* on the *IEA*. See Appendix 1 for variable descriptions. The property type fixed effects are included in the Fama-MacBeth regressions. Firm and time fixed effects are included in the panel regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fama-MacBeth

RetRf	(1) QTR	(2) QTR	(3) QTR	(4) QTR	(5) ANN	(6) ANN	(7) ANN	(8) ANN
PPR (Lag 1)		0.660***				1.307***		
		(3.94)				(2.72)		
aPPR (Lag 1)			0.550***				1.493**	
			(3.20)				(2.00)	
OaPPR (Lag 1)				1.198***				2.755**
				(3.20)				(2.00)
IEA		0.440	0.403	0.365		-1.953**	-2.307*	-2.123*
		(0.94)	(0.83)	(0.73)		(-1.93)	(-1.70)	(-1.68)
Size	-0.121	-0.157	-0.162	-0.162	0.129	0.068	0.123	0.123
	(-0.69)	(-0.91)	(-0.92)	(-0.92)	(0.28)	(0.15)	(0.29)	(0.29)
B/M	1.217	1.359	1.236	1.236	7.796***	8.269***	8.212***	8.212***
	(1.51)	(1.61)	(1.44)	(1.44)	(3.59)	(3.99)	(3.69)	(3.69)
Momentum	0.048***	0.042***	0.044***	0.044***	0.492***	0.494***	0.490***	0.490***
	(3.81)	(3.43)	(3.51)	(3.51)	(8.00)	(7.90)	(8.08)	(8.08)
Leverage	-0.046	-0.534	-0.399	-0.399	6.737	6.990	7.864	7.864
	(-0.03)	(-0.36)	(-0.28)	(-0.28)	(1.33)	(1.41)	(1.60)	(1.60)
Profitability	0.160***	0.170***	0.164***	0.164***	0.131*	0.136*	0.131*	0.131*
	(3.75)	(4.09)	(3.98)	(3.98)	(1.65)	(1.76)	(1.79)	(1.79)
Investment	0.030	0.023	0.024	0.024	0.053	0.062	0.060	0.060
	(0.80)	(0.58)	(0.62)	(0.62)	(0.96)	(1.07)	(1.09)	(1.09)
ILLIQ	-2.998	-4.650	-4.361	-4.361	-4.005	-4.343	-4.012	-4.012
	(-0.52)	(-0.74)	(-0.69)	(-0.69)	(-0.39)	(-0.41)	(-0.38)	(-0.38)
IVOL	-1.396*	-1.319*	-1.288	-1.288	-3.598*	-3.752*	-3.534*	-3.534*
	(-1.79)	(-1.65)	(-1.59)	(-1.59)	(-1.83)	(-1.74)	(-1.77)	(-1.77)
Constant	3.082	0.997	1.129	2.444	2.825	1.321	-1.908	6.271
	(1.40)	(0.41)	(0.46)	(1.00)	(0.66)	(0.31)	(-0.40)	(1.45)
PropFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.354	0.382	0.381	0.381	0.513	0.531	0.534	0.534
# Obs	6,591	6,591	6,591	6,591	1,754	1,754	1,754	1,754

Panel B: Panel

RetRf	(1) QTR	(2) QTR	(3) QTR	(4) QTR	(5) ANN	(6) ANN	(7) ANN	(8) ANN
PPR (Lag 1)		0.595***				1.477**		
		(3.65)				(2.12)		
αPPR (Lag 1)			0.499***				1.512*	
			(3.08)				(1.86)	
OαPPR (Lag 1)				1.086***				2.791*
				(3.08)				(1.86)
IEA		0.204	0.218	0.218		-0.311	-0.175	-0.175
		(0.45)	(0.47)	(0.47)		(-0.20)	(-0.11)	(-0.11)
Size	-4.014***	-4.004***	-4.010***	-4.010***	-6.997***	-6.898***	-7.015***	-7.015***
	(-6.19)	(-6.15)	(-6.19)	(-6.19)	(-3.37)	(-3.28)	(-3.36)	(-3.36)
B/M	5.692**	5.680**	5.681**	5.681**	25.864***	25.979***	26.015***	26.015***
	(2.44)	(2.43)	(2.44)	(2.44)	(5.48)	(5.54)	(5.54)	(5.54)
Momentum	0.043***	0.041***	0.042***	0.042***	0.369***	0.363***	0.365***	0.365***
	(4.30)	(3.96)	(4.09)	(4.09)	(10.05)	(9.81)	(9.72)	(9.72)
Leverage	-1.145	-1.247	-1.134	-1.134	5.342	5.060	5.726	5.726
	(-0.45)	(-0.49)	(-0.45)	(-0.45)	(0.68)	(0.65)	(0.73)	(0.73)
Profitability	0.089***	0.091***	0.089***	0.089***	-0.043	-0.041	-0.041	-0.041
	(3.01)	(3.06)	(2.99)	(2.99)	(-1.13)	(-1.10)	(-1.10)	(-1.10)
Investment	0.003	0.004	0.002	0.002	-0.018	-0.021	-0.020	-0.020
	(0.25)	(0.39)	(0.18)	(0.18)	(-1.13)	(-1.24)	(-1.20)	(-1.20)
ILLIQ	-2.280*	-2.300*	-2.290*	-2.290*	5.325	5.430	5.276	5.276
	(-1.69)	(-1.71)	(-1.70)	(-1.70)	(1.24)	(1.25)	(1.23)	(1.23)
IVOL	-1.563***	-1.551***	-1.556***	-1.556***	-6.866***	-6.807***	-6.820***	-6.820***
	(-2.86)	(-2.84)	(-2.87)	(-2.87)	(-2.75)	(-2.68)	(-2.67)	(-2.67)
Constant	27.382***	25.405***	25.615***	26.761***	41.549**	38.032**	37.838**	41.350**
	(4.47)	(4.08)	(4.13)	(4.38)	(2.38)	(2.18)	(2.18)	(2.41)
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.539	0.540	0.540	0.540	0.646	0.648	0.648	0.648
# Obs	6,591	6,591	6,591	6,591	1,754	1,754	1,754	1,754

Table 4: Long-Horizon Predictability of Property Portfolio Returns

This table reports *h*-period-ahead return predictability of *aPPR*. Fama-MacBeth results based on quarterly datasets. *RetRf* is the chain-linked monthly stock returns of firm *i* in period *t* in excess of the rate of return of 30-day Treasury bills. *aPPR* is the residual from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities. See Appendix 1 for variable descriptions. Control variables are the same as in Table 3 and suppressed for brevity. Property type fixed effects are included in the regression. The numbers in parentheses are *t*-statistics. The *t*-statistics computed with the Newey-West (1987) standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

RetRf (Qtr)	(1)	(2)	(3)	(4)	(5)
aPPR (Lag 1 Qtr)	0.582***				
	(3.46)				
aPPR (Lag 2 Qtr)		0.656***			
		(3.37)			
aPPR (Lag 3 Qtr)			0.537**		
			(2.61)		
aPPR (Lag 4 Qtr)				0.466**	
				(2.63)	
aPPR (Lag 5 Qtr)					0.354*
					(1.73)
IEA	0.403	0.606	0.185	0.653	0.503
	(0.83)	(1.26)	(0.34)	(1.47)	(1.08)
Controls	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes
R-squared	0.386	0.388	0.393	0.388	0.393
# Obs	6,255	6,255	6,255	6,255	6,255

Table 5: Regressions of Unlevered Returns on Property Portfolio Returns

This table shows regression results on the relationship between REIT unlevered returns and property portfolio returns. *UnlevRet* is the unlevered returns of firm *i* in period *t*, calculated using the Ling and Naranjo (2015) method. *aPPR* is the residual from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities. *OaPPR* is the residual from a regression of *aPPR* on the *IEA*. See Appendix 1 for variable descriptions. Control variables are the same as in Table 3 and suppressed for brevity. Property type fixed effects are included in Fama-MacBeth regressions in Columns (1), (2), (5), and (6). Firm and time fixed effects are included in panel regressions in Columns (3), (4), (7), and (8). Standard errors are calculated using the Newey-West (1987) method in Fama-MacBeth (1973) regressions and clustered at firm level in panel regressions. The numbers in parentheses are *t*-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FM	FM	Panel	Panel	FM	FM	Panel	Panel
UnlevRet	QTR	QTR	QTR	QTR	ANN	ANN	ANN	ANN
aPPR (Lag 1)	0.220***		0.244***		0.946**		0.795***	
	(3.60)		(4.24)		(2.33)		(2.91)	
OaPPR (Lag 1)		0.484***		0.538***		1.699**		1.427***
		(3.60)		(4.24)		(2.33)		(2.91)
IEA	0.399*	0.374*	-0.087	-0.087	0.034	0.044	-0.223	-0.223
	(1.91)	(1.81)	(-0.50)	(-0.50)	(0.04)	(0.05)	(-0.36)	(-0.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	No	No	Yes	Yes	No	No
FirmFE	No	No	Yes	Yes	No	No	Yes	Yes
TimeFE	N/A	N/A	Yes	Yes	N/A	N/A	Yes	Yes
R-squared	0.312	0.312	0.534	0.534	0.477	0.477	0.605	0.605
# Obs	5,882	5,882	5,882	5,882	1,594	1,594	1,594	1,594

Table 6: Regressions on Property Turnover and Property Portfolio Returns

This table shows the results of Fama-MacBeth (1973) regression analysis. Results in Columns (1)-(3) ((4)-(6)) are based on quarterly (annual) sample of 6,591 firm-quarter (1,754 firm-year) observations from 1996-2018. The dependent variable, *RetRf*, is the chain-linked monthly stock returns of firm *i* in period *t* in excess of the rate of return of 30-day Treasury bills. *aPPR* is the residual from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities. *PropTO* is the average of MSA-level property market turnover, weighted by REIT allocation to each MSA. See Appendix 1 for variable descriptions. Control variables are the same as in Table 3 and suppressed for brevity. The property type fixed effects are included in the regression. The *t*-statistics computed with the Newey-West (1987) standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
RetRf	QTR	QTR	QTR	ANN	ANN	ANN
aPPR (Lag 1)	0.550***		0.543***	1.490***		1.634***
	(3.20)		(3.11)	(3.37)		(3.45)
PropTO (Lag 1)		0.295	1.412		8.093	11.267
		(0.26)	(1.03)		(1.36)	(1.21)
IEA	0.403	0.636	0.542	-2.251**	-2.252*	-2.878**
	(0.83)	(1.40)	(1.17)	(-2.05)	(-1.79)	(-2.41)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.381	0.381	0.393	0.529	0.530	0.538
# Obs	6,591	6,591	6,591	1,754	1,754	1,754

Table 7: Regressions of Excess Returns on Appreciation and Income Returns

This table shows Fama-MacBeth (1973) regression on the relationship between REIT excess returns and property portfolio appreciation and income return alphas. *RetRf* is the chain-linked monthly stock returns of firm *i* in period *t* in excess of the rate of return of 30-day Treasury bills. *aPPR PRC* is the residual from the cross-sectional regressions of quarterly property portfolio appreciation returns on the return sensitivities. *aPPR INC* is the residual from the cross-sectional regressions of quarterly property portfolio income returns on the return sensitivities. See Appendix 1 for variable descriptions. Control variables are the same as in Table 3 and suppressed for brevity. The property type fixed effects are included in the regression. The numbers in parentheses are *t*-statistics. The *t*-statistics computed with the Newey-West (1987) standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
RetRf (Qtr)	QTR	QTR	QTR	ANN	ANN	ANN
aPPR PRC (Lag 1)	0.487***		0.520***	1.613**		1.448**
	(2.68)		(2.74)	(2.15)		(2.00)
aPPR INC (Lag 1)		0.719	1.408		-2.208	-1.326
		(0.73)	(1.19)		(-0.85)	(-0.51)
IEA	0.308	0.655	0.447	-2.065	-2.176	-2.451
	(0.62)	(1.34)	(0.88)	(-1.64)	(-1.45)	(-1.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.382	0.389	0.404	0.534	0.530	0.541
# Obs	6,591	6,591	6,591	1,754	1,754	1,754

Table 8: Regression Results of NOI Growth on Property Portfolio Returns

This table shows Fama-MacBeth (1973) regression results on the relationship between same-store NOI growth and *aPPR*. The dependent variable, *SS NOI Growth*, is the percentage change in net operating income from the previous period on properties owned for the entire current period and in the entire previous period. *aPPR* is the residual from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities. *aPPR PRC* is the residual from the cross-sectional regressions of quarterly property portfolio appreciation returns on the return sensitivities. *aPPR INC* is the residual from the cross-sectional regressions of quarterly property portfolio income returns on the return sensitivities. See Appendix 1 for variable descriptions. Control variables are the same as in Table 3 and suppressed for brevity. The property type fixed effects are included in the regression. The numbers in parentheses are *t*-statistics. The *t*-statistics computed with the Newey-West (1987) standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
RetRf (Qtr)	QTR	QTR	ANN	ANN
aPPR (Lag 1)	0.672***		0.724***	
	(3.41)		(2.91)	
aPPR PRC (Lag 1)		0.647***		0.876**
		(4.04)		(2.28)
aPPR INC (Lag 1)		-0.085		-2.436
		(-0.08)		(-1.52)
IEA	0.779**	1.042***	0.349	0.017
	(2.50)	(3.63)	(0.65)	(0.02)
Controls	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes
R-squared	0.432	0.469	0.435	0.478
# Obs	3,869	3,869	1,012	1,012

Table 9: Summary Statistics by Market Tiers

This table shows summary statistics (number of observations, mean, standard deviation (SD), and 25th, 50th, and 75th percentiles) of firm-level property portfolio returns decomposed by gateway, secondary and tertiary markets. See Appendix 1 for variable descriptions. The number of observations equals 5,693.

	Mean	SD	P25	P50	P75
PPR (Gateway)	2.53	2.63	1.64	2.57	3.66
PPR (Non-gateway)	2.22	2.19	1.65	2.46	3.20
PPR (Secondary)	2.23	2.09	1.65	2.34	3.17
PPR (Tertiary)	2.19	2.37	1.60	2.35	3.19
aPPR (Gateway)	2.56	2.52	1.62	2.56	3.62
aPPR (Non-gateway)	2.17	2.19	1.61	2.43	3.17
aPPR (Secondary)	2.21	2.11	1.64	2.33	3.13
aPPR (Tertiary)	2.14	2.36	1.54	2.33	3.20
PropTO	1.65	2.11	0.04	1.06	2.50

Table 10: Decomposition by Market Tiers

This table shows Fama-MacBeth (1973) regression results on the relationship between REIT excess returns and property portfolio returns decomposed by gateway, secondary and tertiary markets. The dependent variable, *RetRf*, is the chain-linked monthly stock returns of firm *i* in period *t* in excess of the rate of return of 30-day Treasury bills. *aPPR* is the residual from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities. See Appendix 1 for variable descriptions. Control variables are the same as in Table 3 and suppressed for brevity. The property type fixed effects are included in the regression. The *t*-statistics computed with the Newey-West (1987) standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

RetRf (Qtr)	(1)	(2)	(3)	(4)	(5)
aPPR (Lag 1)	0.835***				
	(4.03)				
aPPR (Gateway)		0.480***			0.450***
		(3.21)			(3.10)
aPPR (Secondary)			0.359**		0.273*
			(2.02)		(1.77)
aPPR (Tertiary)				0.219*	0.130
				(1.89)	(1.04)
IEA	0.659	0.630	0.994*	0.756	0.679
	(1.28)	(1.20)	(1.80)	(1.44)	(1.32)
Controls	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes
R-squared	0.404	0.408	0.403	0.403	0.434
# Obs	5,693	5,693	5,693	5,693	5,693

Appendix 1: Variable Definitions

Variable	Source	Definition
REIT Returns		
RetRf$_{i,t}$	CRSP	The chain-linked monthly stock returns of firm *i* in period *t* in excess of the rate of return of 30-day Treasury bills.
CAPM Alpha$_{i,t}$	CRSP	The chain-linked monthly risk-adjusted returns of firm *i* in period *t* based on the market factor model.
FF3 Alpha$_{i,t}$	CRSP	The chain-linked monthly risk-adjusted returns of firm *i* in period *t* based on the Fama-French (1993) factor model.
Carhart Alpha$_{i,t}$	CRSP	The chain-linked monthly risk-adjusted returns of firm *i* in period *t* based on the Carhart (1997) factor model.
UnlevRet$_{i,t}$	Compustat, S&P Global	The unlevered returns of firm *i* in period *t*, calculated using the Ling and Naranjo (2015) method.
GSQ$_{i,t}$	Green Street	The ratio of the market value of common equity, operating partnership units, in-the-money options, and total liabilities to the sum of net asset value and the market value of total liabilities of firm *i* in year *t*.
Property Portfolio Returns		
PPR$_{i,t}$	NCREIF, S&P Global	The raw property portfolio returns of firm *i* in period *t*, calculated as the average of NCREIF NPI property-MSA sub-indices, weighted by the percentage of the REIT's portfolio allocated to each property type in each MSA.
aPPR$_{i,t}$	NCREIF, S&P Global	Property portfolio alphas, or the residuals from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities to the national level NCREIF NPI excess returns and property turnovers, and on the sensitivities to the five common risk factors market, 10-year Treasury bond excess returns, size, value (Fama and French, 1993), and momentum (Carhart, 1997).
OaPPR$_{i,t}$	NCREIF, S&P Global	The residual from a regression of property portfolio alphas on the orthogonalized regional economic activity indices.
Channels		
aPPR PRC$_{i,t}$	NCREIF, S&P Global	Property portfolio appreciation return alphas, or the residuals from the cross-sectional regressions of raw quarterly property portfolio appreciation returns on the return sensitivities to the national level NCREIF NPI excess returns and property turnovers, and on the sensitivities to the five common risk factors market, 10-year Treasury bond excess returns, size, value (Fama and French, 1993), and momentum (Carhart, 1997).
aPPR INC$_{i,t}$	NCREIF, S&P Global	Property portfolio income return alphas, or the residuals from the cross-sectional regressions of raw quarterly property portfolio income returns on the return sensitivities to the national level NCREIF NPI excess returns and property turnovers, and on the sensitivities to the five common risk factors market, 10-year Treasury bond excess returns, size, value (Fama and French, 1993), and momentum (Carhart, 1997).

Appendix 1 (cont')

Variable	Source	Definition
SS NOI Growth$_{i,t}$	S&P Global	Same-store net operating income growth of firm *i* during period *t*, defined as the percentage change in net operating income from the previous period on properties owned for the entire current period and in the entire previous period.
Control Variables		
IEA$_{i,t}$	Federal Reserve	The orthogonalized regional economic activity indices, calculated using the Smajlbegovic (2019) method.
Size$_{i,t}$	Compustat	The logarithm of the product of stock price and shares outstanding.
B/M$_{i,t}$	Compustat	The ratio of book equity to market equity.
Momentum$_{i,t}$	CSRP	Cumulative stock returns over the past twelve months (in percentage).
Leverage$_{i,t}$	Compustat	Sum of total long-term debt and debt in current liabilities divided by total assets.
Profitability$_{i,t}$	Compustat	Revenues minus revenues minus cost of goods sold, interest expense, and selling, general, and administrative expense divided by the sum of book equity and minority interest at the end of the previous period (in percentage).
Investment$_{i,t}$		The percentage growth rate in non-cash assets of firm *i* during period *t*.
ILLIQ$_{i,t}$	CRSP	The logarithm of the average Amihud (2002) daily volume price impact firm *i* during period *t*.
IVOL$_{i,t}$	CRSP	The standard deviation of residuals of monthly Fama-French 3-factor-model regressions of daily stock returns (in percentage).
δ_i		Firm fixed effects.
PropFE		Property type fixed effects.
θ_t		Time fixed effects (year or year-quarter).
Market Tiers		
Gateway		Gateway markets include Boston, Chicago, Los Angeles, New York, San Francisco and Washington, D.C.
Secondary		Secondary markets include Atlanta, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Miami, Minneapolis, Orlando, Philadelphia, Phoenix, Portland, Sacramento, St. Louis, San Antonio, San Diego, Seattle, and Tampa.
Tertiary		MSAs that are neither gateway nor secondary markets.

Appendix 2: Reverse Causation Checks

This appendix shows Fama-MacBeth (1973) regression results on the relationship between property portfolio returns and REIT excess returns. *aPPR* is the residual from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities. *RetRf* is the chain-linked monthly stock returns of firm *i* in period *t* in excess of the rate of return of 30-day Treasury bills. See Appendix 1 for variable descriptions. Control variables are the same as in Table 3 and suppressed for brevity. Property type fixed effects are included in the regression. The numbers in parentheses are *t*-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
aPPR	QTR	QTR	QTR	QTR	QTR	ANN	ANN	ANN	ANN	ANN
RetRf (Contemp)	0.001					-0.004				
	(0.63)					(-0.80)				
RetRf (Lag 1)		-0.002					0.001			
		(-1.01)					(1.06)			
RetRf (Lag 2)			-0.001					-0.000		
			(-0.49)					(-0.15)		
RetRf (Lag 3)				0.005					0.001	
				(1.56)					(1.30)	
RetRf (Lag 4)					-0.001					0.000
					(-0.34)					(0.05)
IEA	0.534***	0.542***	0.556***	0.528***	0.589***	0.470*	0.441*	0.445*	0.440**	0.374**
	(3.34)	(3.20)	(3.20)	(3.36)	(3.05)	(2.04)	(1.95)	(2.02)	(2.09)	(2.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.297	0.294	0.296	0.299	0.299	0.397	0.394	0.393	0.411	0.417
# Obs	6,591	6,591	6,591	6,591	6,591	1,754	1,754	1,754	1,754	1,754

Appendix 3: Robustness Tests

This table shows Fama-MacBeth (1973) regression results on the relationship between quarterly property portfolio returns and REIT excess returns. *aPPR* is lagged the residual from the cross-sectional regressions of raw quarterly property portfolio returns on the return sensitivities. *RetRf,* is the chain-linked quarterly stock returns of firm *i* in period *t* in excess of the rate of return of 30-day Treasury bills. *Characteristic* represents firm size in column (1), S&P in column (2), institutional ownership in column (3) and crisis period in column (4). See Appendix 1 for variable descriptions. Control variables are the same as in Table 3 and suppressed for brevity. Property type fixed effects are included in the regression. The numbers in parentheses are *t*-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

RetRf (Qtr)	(1) Size	(2) S&P500	(3) Institutional Ownership	(4) Crisis
aPPR	0.451***	0.427***	0.394**	0.439***
	(2.83)	(2.76)	(2.48)	(3.84)
*aPPR*Characteristic*	-1.038	1.396	0.307	2.197
	(-1.10)	(1.24)	(0.67)	(1.07)
Characteristic	-0.234	-0.241	-0.054	0.020
	(-0.88)	(-0.49)	(-0.31)	(0.44)
IEA	0.207	-0.652	-0.626	-0.253
	(0.37)	(-0.54)	(-0.67)	(-0.32)
Controls	Yes	Yes	Yes	Yes
Property type fixed effects	Yes	Yes	Yes	Yes
R-squared	0.451	0.476	0.474	0.434
No. of observations	4,635	4,635	4,635	4,635