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

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Abstract

An extensive literature finds that indices of returns on equity real estate investment trusts (REITs) predict return indices in the private commercial real estate (CRE) market. Using a novel geographically weighted proxy for the quarterly performance of the property types within the local markets in which a REIT is invested, or property portfolio return (*PPR*), we find a "private predicts public" result in a cross-sectional, firm-level context. This finding suggests that geographically dispersed information and investors' limited attention can delay timely stock price adjustments. Our findings also suggest it is the diffusion of information about "local" price changes, rather than local supply elasticities, regulatory constraints, the degree of local information risk, current rental income, or local liquidity that predicts REIT returns. The *PPR*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 speed at which "local" information about the perceived productivity of a firm's assets is capitalized into stock prices.

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

JEL classification: G11, G12, D82, R11

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1. Introduction

An extensive literature exists on the relation between private and public market commercial real estate (CRE) returns (e.g., Riddiough et al., 2005; Pagliari et al., 2005; Boudry et al., Yunus et al., Muhlhofer, 2013; Ling and Naranjo, 2015). Using index-level data, these studies find returns on equity real estate investment trusts (REITs) predict returns in the private CRE market; however, the reverse is not true. This "public predicts private" result found in time-series studies is generally attributed to imperfections in the private CRE market that are exacerbated by the use of aggregate national indices based on lagged and smoothed estimates of price appreciation among the constituent properties. Although a less extensive literature exists on the predictability of firm-level REIT returns (Nelling and Gyourko, 1998; Ling et al., 2000; Guidolin et al., 2020), no prior work has examined whether information on the return performance of the local private markets in which listed REITs are invested is predictive of REIT returns.

In contrast to the "public predicts private" result documented in the time-series, index-level studies, we find a "private predicts public" result in a cross-sectional, firm-level, context using a novel geographically weighted proxy for the quarterly performance of the local markets in which a REIT is invested. We call this proxy the firm's property portfolio return (*PPR*). Why is the direction of predictability reversed in a cross-sectional context? The answer lies in the growing literature on the importance of a firm's geographic footprint in the return-generating process. For example, evidence suggests that market participants are unable to incorporate all value-relevant information about the foreign operations of multinational firms into stock prices (Thomas, 2000; Li et al., 2014; Huang, 2015). A related literature finds that firm-specific information about the geographic concentration of firms' economic activities can be used to predict stock returns (e.g., Garcia and Norli, 2012; Bernile et al., 2015). Smajlbegovic (2019) finds that economic activity in regions that are economically relevant to industrial companies helps predict the cross-section of stock returns. 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.

The geographical variation in an equity REIT's economic interests can generate persistent information asymmetry among investors (Ling et al., 2019b). An average REIT owns properties in six different states and twelve different metropolitan statistical areas (MSAs). In addition, many REITs invest in multiple property types. The speed at which market participants capitalize the performance of the office market performance in New York into the stock prices of REITs that own New York office properties may differ from the retail market in Orlando. Moreover, the inability of investors to immediately price all value-relevant information about the performance of local markets in which firms are invested could generate persistent return predictability in the cross-section of listed REIT returns. We present evidence consistent with a diffusion of geographic-based information into stock prices.

Examination of the extent to which local information about the perceived 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. We improve on the measurement of a firm's geographic footprint and the measurement of economically relevant activity in local markets to which a firm is exposed by focusing our analysis on publicly-traded REITs. The tangible real assets owned by equity REITs are relatively easier to locate and value than the properties, factories, equipment, and intangible assets of non-real estate firms. This provides a relatively clean setting for identifying the relation between firms' geographic footprints and stock returns. Importantly, income-producing real estate, whose performance depends on the rents paid by local tenants, is classified as a non-tradable industry, which makes it easier to measure the impact of local economic growth on investment returns (Mian and Sufi, 2014).[1]

We first measure a firm's asset portfolio exposure to each 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 CRE markets to measure the performance of the CRE markets to which a given REIT is exposed equity REITs 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-level NCREIF returns and the MSA portfolio weights obtained from S&P Global data, we construct a time-series proxy (*PPR*) for the private market returns earned by investors in properties similar to those owned by the REIT and located in the same local markets in which the REIT is invested. This approach implicitly assumes returns on the properties in a REIT's portfolio are correlated with local market-level averages and does not capture any cross-firm variation in property selection or on-going property management skills.

To examine the relation between *PPR*s and REIT returns, we first sort REITs into *PPR* 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 *PPR*s in the prior period. Using a trading strategy of taking a long position

[1] We thank an anonymous referee for this helpful comment.

in the highest tercile *PPR* firms and short position in the lowest tercile of *PPR* firms yields a statistically and economically significant positive return of 0.41% to 1.88% over the next quarter, depending on the asset pricing model employed for risk adjusting returns.

Using both cross-sectional and panel regression techniques with standard firm-level control variables, we next investigate the extent to which firm-level *PPR*s predict returns in the equity REIT market. It is possible that REIT returns are driven, at least in part, by the liquidity of the local markets in which REITs are invested, as well as the level of economic activity in these local markets. To avoid the omission of local private market variables potentially correlated with *PPR*, we include proxies for the liquidity and economic activity in each market in which the REIT owns properties. These local market risk exposures, weighted by our time-varying measures of each REIT's portfolio exposure in each MSA, have no predictive power and do not absorbed *PPR*s explanatory power. We also perform robustness tests that focus on other local risk factors, proxied by land supply elasticity (Saiz, 2010), land use regulation (Gyourko et al., 2008), and the percentage of total property value in the MSA that represents land (Kurlat, 2016; Kurlat & Stroebel, 2015).. These additional tests do not support a risk-based explanation for the predictability of *PPR*.

Our baseline results indicate that quarterly lags of *PPR* predict returns in the public REIT market in the subsequent quarter. Moreover, we find that two-quarter, three-quarter, and four-quarter lags of *PPR*s also predict equity REIT returns in quarter *t*. Given the well-known smoothing and lagging associated with reported private market (NCREIF NPI) returns, we also use the quarterly residuals from a predictive model of *PPR* and find that these *PPR* innovations are also highly predictive of returns in the subsequent quarter.

Our results are robust 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. We also "de-lever" REIT returns to remove the effects of financial leverage and find similar results, suggesting that changes in debt financing do not explain the predictive power of *PPR* we document.

We also use *PPR* as the dependent variable and regress it on lagged firm-level REIT returns and our set of controls. We find no "reverse" predictability at the firm level.

We next investigate other potential mechanisms that can explain the persistent ability of our *PPR* measure to predict REIT returns. First, we decompose quarterly *PPR*s into an income return component and a price appreciation component. We find a significant positive link between geographically weighted local price appreciation and REIT returns but find no relation between local income returns and subsequent REIT returns. We also find a positive and significant relation between local price appreciation and REITs' "same-store" rental growth. This suggests that the ability of *PPR* to predict REIT returns is not purely driven by changes in the property portfolio composition of REIT portfolios.

Given 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 *PPR* 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 during our sample period have outperformed allocations to non-gateway markets (Ling et al., 2019a). More importantly, the information about price appreciation in gateway markets released each quarter by NCREIF better explains firm-level REIT returns than information about the performance of the more income-orientated secondary and tertiary markets.

Lastly, we explore the nature of frictions that could delay a speedy adjustment of REIT returns to private market returns. Because the variation of our *PPR* measure is largely driven by cross-sectional differences in REITs' geographically dispersed property holdings, we posit that the predictability we document is likely explained by geographic impediments to information collection and/or investors' limited attention, both of which constrain investors' information gathering and processing ability (e.g., Lou, 2014; Fang and Peress, 2009; Da et al., 2011). By constructing trading strategies that explore investors' attention and local bias, we show the *PPR* predictability is stronger for less visible firms and for firms with high local institutional ownership.

This evidence is consistent with our conjecture that market participants are unlikely to fully incorporate geographically dispersed information.

To definitively conclude that local *PPRs* have a causal effect on REIT returns, we would need to identify pure exogenous shocks to local information environments. Although our analysis is primarily cross-sectional and not causal, the robustness of our results to alternative explanations is consistent with theory stating that market frictions in relatively illiquid and highly segmented local real estate markets may impede the timely capitalization of changing cash flow expectations into firm values and returns.

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

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.[2]

To capture the economic environments 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) uses similar state-level indexes,

[2] 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. A recent paper by Addoum et al. (2020) improves on those limitations by studying the impact of temperature shocks on sales and productivity using detailed establishments data.

multiplied by the 10-K citation shares for each state, to produce a quarterly weighted average measure of each firm's exposure to "local" economic activity.[3]

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, 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 is likely to be larger for firms that employ more capital (less labor) in their production function or have a relatively high percentage of (difficult to value) intangible assets. Moreover, the number of times a state's name is mentioned in a firm's 10-K report may not directly identify the state's economic significance to the firm.[4]

To improve on the measurement of a firm's geographic footprint and the measurement of economically relevant activity in local markets, we construct a quarterly time-series of unlevered property portfolio returns, *PPR*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 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.[5] These MSA-level NCREIF NPI returns are then

[3] Data limitations often prevent researchers from constructing precise measures for variables of interest or to completely rule out measurement errors. It is therefore common to construct proxies for these variables. For example, Gompers et al. (2003) measure the strength of shareholder rights using 24 corporate governance provisions. In Korniotis and Kumar (2013) and Smajlbegovic (2019), the state coincident economic activity index, a proxy for local economic activities, is a composite of four labor market indicators, including nonfarm payroll employment, the unemployment rate, average hours worked in manufacturing and wages and salaries.

[4] 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.

[5] Established in 1982, NCREIF is a not-for-profit institutional real estate industry association that collects, processes, validates, and disseminates information on the risk/return characteristics of commercial real estate assets owned by institutional (primarily pension and endowment fund) investors. NCREIF's flagship index, the

value-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 *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 a proxy for the unlevered total returns earned by a portfolio of properties similar to each REIT's underlying portfolio.[6]

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).

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. We also employ annual NPI returns, which substantially reduces any appraisal smoothing (see Geltner 1993). 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 performance of similar properties located in the same markets in which the REIT is invested. In fact,

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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.

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

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.[7]

2.3 Do PPRs Predict Stock Returns?

To investigate the extent to which *PPRs* 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:

$$Ret_{i,q} - r_{f,q} = \alpha_q + \beta_q PPR_{i,q-1} + \gamma_q PropTO_{i,q-1} + \vartheta_q IEA_{i,q-1} + \mathbf{X'}_{\boldsymbol{i,q-1}}\mathbf{b}_{\boldsymbol{q}} + \delta_i + \theta_q + \varepsilon_{i,q} \tag{1}$$

where $Ret_{i,q} - r_{f,q}$ is the return in excess of the risk-free rate in quarter q. Our test variable, $PPR_{i,q-1}$, is the lagged quarterly property portfolio returns in quarter *q-1*.

It is possible that the ability of *PPR* to predict REIT returns could be driven, at least in part, by the correlation of *PPR* with liquidity and/or the strength of economic activity in the local markets. For example, 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. Korniotis and Kumar (2013) and Smajlbegovic (2019) show that local economic activities are correlated with stock returns. We therefore include a lagged geographically weighted turnover measure for the private market

[7] Chambers et al. (2021) discuss potential measurement problems associated with the estimation of long-term real estate performance. For example, when estimating historical rental income growth rates, one might not be able to control for changes in the quality mix of properties over time and the use of aggregate national data might exacerbate this problem. In this analysis, we construct firm-level *PPR*s using disaggregate, MSA-level sub-indices for each major property type. We also employ cross-sectional regression techniques to examine the return predictability of *PPR*s.

($PropTO_{i,q-1}$) and a measure of the local economic activity to which the REIT's portfolio is exposed (IEA) as control variables. In equation (1), $IEA_{i,q-1}$ is the lagged weighted average measure of economic activity at either state- or MSA-level.

$\mathbf{X'}_{\boldsymbol{i,q-1}}$ represents firm-level determinants of the cross-section of REIT returns, measured at the end of the quarter (or year) prior to when returns are measured. δ_i represents property fixed effects that control for the property type focus of the REIT in Fama–MacBeth cross-sectional regressions and firm fixed effects in panel regressions. θ_q represents time fixed effects in a panel regression setting. $\varepsilon_{i,q}$ is a standard error term.

If the estimated coefficient on $PPR_{i,q-1}$, 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, 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: 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. Total returns on a broad-based stock market portfolio and the risk-free rate, along with Size, Value, and Momentum risk factors, are obtained from Ken French's website.[8] Proxies for private market CRE returns and the data needed to construct a quarterly estimate of property turnover at the local level are obtained from NCREIF. The NCREIF Property Indices (NPI) are estimated unleveraged composite total returns for private CRE properties held for investment purposes.

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

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. 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 each quarter separately for each property type owned by the REIT. This produces a proxy, based on similar properties, for the quarterly return on each REIT's underlying property portfolio.[11] Given the high degree of persistence in

[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] 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.

[11] In some cases, the needed MSA-level return index for a particular property type is not available from NCREIF if there are not enough properties to provide data suppliers anonymity. For example, assume that a REIT owned an office property in Indianapolis, Indiana in the 4^{th} quarter of 2015. However, the NCREIF NPI does not contain a return index for Indianapolis office properties in the 4^{th} quarter of 2015. We would then substitute the return index for office properties in the state of Indiana.

reported private market real estate returns, we also measure innovations in *PPR* by orthogonalizing *PPR* with respect to lagged *PPR*s over the past four quarters. *PPR* innovations are uncorrelated with past performance and therefore are likely to be more informative.[12]

To control for the liquidity in the private markets to which the REIT's portfolio is exposed, we follow Downs and Zhu (2019) and construct, for each firm-quarter, a weighted average of the turnover in each market in which the REIT owns properties (*PropTO*). The weights are each firm's 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.[13]

We measure local economic activity at the state or MSA level. Our state-level macroeconomic variable is developed using the State Coincident Indexes (SCIs), developed by Crone and Clayton-Matthews (2005). The SCI is a 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 a 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 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. We also downloaded yearly data on gross domestic product and personal income at the MSA level from the

[12] We thank an anonymous referee for this suggestion.

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

Bureau of Economic Analysis (BEA) website.[14] These MSA-level macroeconomic variables, available beginning in 2001, are used to conduct a robustness analysis.

Our firm-level 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 of the stock's Amihud (2002) illiquidity measure,[15] *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. Our final dataset contains 6,591 firm-quarter observations. See Appendix 1 for variable descriptions.

4. Results

4.1 PPR 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. The quarterly mean of *PPR* is 2.30%, with a standard deviation of 2.21%. Although not separately tabulated, the quarterly *PPR* means for each of the five property types range from 2.17% to 2.35%; the standard deviations range from 1.93% to 2.42%. Thus, we observe little difference in *PPR* across property types. The mean of *PPR Innovation* is -0.01%. The 25th percentile is -0.48%; the 75th percentile is 0.56%.

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[14] https://apps.bea.gov/regional/downloadzip.cfm (Accessed on 01/11/2021).

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

Figure 1 plots the distribution of quarterly *PPR*s over the 1996-2018 sample period. For comparison, the total quarterly return on the NCREIF NPI is also included (the dash line). As expected, when averaged across all REITs in our sample, we observe small return differences between *PPR*s and the NCREIF NPI. However, the 95% confidence bands around the mean *PPR*s suggest that the *PPR*s of individual REITs vary substantially from the return on the NCREIF NPI. These differences reflect the extent to which the specific local markets in which a REIT invest affects performance.

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 sort REITs into *PPR* 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 raw returns and risk-adjusted returns for *PPR*-based portfolios using various asset pricing models.

The quarterly results reported in Panel A of Table 2 suggest that the relationship between lagged *PPR* measures and REIT returns increases monotonically in *PPR*. A portfolio strategy that is long the highest and short the lowest *PPR* tercile yields a statistically and economically significant positive return of 1.88% when using raw REIT returns.[16] When we calculate risk-adjusted returns using the CAPM, the Fama-French (1993) three-factor, and the Carhart (1997) four-factor models, a long-short strategy produces quarterly risk-adjusted returns that range from 0.41% to 0.44%, all of which are statistically and economically significant. The results presented in Panels B of Table 2 are based on annualized *PPR*s and subsequent annual REIT returns. Overall, these univariate portfolio sorts suggest that *PPR*s are highly predictive of subsequent REIT returns.

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

4.3 Baseline Regression Results

To examine in a multivariate setting the extent to which property portfolio returns explain variation in excess REIT returns (*RetRf*), we estimate equation (1) using both quarterly Fama–MacBeth cross-sectional regressions and panel regressions. The results are reported in Table 3. Property type fixed effects are included in the regression. *t*-statistics computed with the Newey-West (1987) standard errors are reported in parentheses.

As a starting point, we first estimate equation (1) without our main variable of interest, *PPR,* and without our controls for local market liquidity (*PropTO*) and economic activity (*IEA*). These 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 returns, while idiosyncratic stock price volatility is negatively related to total returns.[17]

In model (2), *PPR* and *IEA* are added as explanatory variables. The estimated coefficient on the one-quarter lag of *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 1.12 percentage points, or a 44% increase relative to its mean (2.53%). The estimated coefficient on *IEA* cannot be distinguished from zero, which indicates that REIT returns are not related to the local economic activity to which the firm is exposed. In model (3), we add *PropTO* to the specification. The estimated coefficient on *PPR* remains positive and highly significant: a change in *PPR* from the bottom to the top quartile is associated with a 1 percentage point increase in quarterly *RetRf*. The estimated coefficients on *PropTO* and *IEA* are not statistically significant.

Models (4) through (6) contain the results from estimating equation (1) using panel regressions. Both firm and quarter fixed effects are included in the

[17] In the untabulated results, we include the national-level NCREIF return index in our cross-sectional regressions, both separately and together with *PPR*. We find that the estimated coefficient on *PPR* is positive and highly significant even when the national level NCREIF return index is included. However, the coefficients on the national level NCREIF return index are not significant.

specifications. The estimated coefficient on *NPI* remains insignificant, while the coefficients on *PPR* remain positive and highly significant in models (5) and (6). The estimated coefficients on *PropTO* and *IEA* indicate no role for these variables in explaining REIT returns, which suggests our positive coefficient estimate on *PPR* does not result from its correlation with local risk factors driven by property market liquidity and local economic activities. Taken together, the results displayed in Table 3 provide strong evidence that the NCREIF reported returns (productivity) of similar assets located in the same markets as the REITs property portfolio are highly predictive of future stock returns.

We next investigate the persistence and speed at which the information contained in *PPR* is absorbed in stock prices. The results of these Fama-MacBeth regressions are displayed in Table 4. Regression control variables are the same set as previously employed, but their coefficient estimates are suppressed for brevity. The results reported as model (1) follow our baseline specification (model (3) in Table 3) in which *PPR* is lagged one quarter. In models (2) through (5) we lag *PPR* two quarters, three quarters, four quarters, and five quarters, respectively. For lags up to five quarters, the estimated coefficient on *PPR* remains positive and significant, although statistical significance is somewhat muted with longer lags. These results demonstrate persistence in the ability of *PPR* to explain the cross-section of REIT returns.

The persistence (auto-correlation) of our private-market property returns raises an additional question: do *future* values of *PPR* also predict REIT returns? To address this issue, we regress REIT returns at time t on contemporaneous and future quarterly values of *PPR*. These results are reported in Appendix 2. Although the estimated coefficient on PPR_{t-1} remains positive and highly significant, the coefficient estimates for PPR_t through PPR_{t+4} cannot be distinguished from zero. These results provide additional support for a “private predicts public” interpretation of our results.

4.4 More Robustness Tests

The high degree of persistence in private market returns may lead to predictability in our *PPR* measure. To address this issue, we regress the NCREIF NPI returns for each property type, and each MSA on the NPI returns in the previous four quarters. From this series of regressions, we predict the total return for each property type in each MSA. We define *PPR Innovation* as the the quarterly return reported by NCREIF for each property type and MSA minus the return predicted by our regression model.

Model (1) in Table 5 reproduces our baseline Fama-MacBeth results from Table 3. In model (2), we replace *PPR* with *PPR Innovation*. *PropTO* and *IEA*, property type fixed effects, as well as our full set of firm-level controls, are included. The estimated coefficient on *PPR Innovation* is positive, highly significant, and larger in magnitude than the corresponding estimate on "raw" *PPR*. The estimated coefficients on *PropTO* and *IEA* continue to indicate no role for these variables in explaining the cross-section of REIT returns. Model (3) in Table 5 reproduces our baseline panel regression results from Table 3. In model (4), we continue to find that *PPR Innovation* predicts REIT returns.

Our findings thus far suggest that *PPR*s predict the cross-section of returns in the public REIT market, suggesting a 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 *PPR*s represent unlevered returns, which may therefore distort the prediction of levered REIT returns.

To investigate this issue, we "delever" firm-level REIT returns to remove the effects of financial leverage following the procedure employed by Ling and Naranjo (2015).[18] As shown by the results reported in Table 6, the estimated coefficients on

[18] 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.

PPR remain positive and significant. This suggests that increases in debt financing that result from price appreciation in the REIT's underlying property portfolio are not driving the ability of *PPR* to predict the cross-section of REIT returns.

Prior studies using *index*-level (aggregate) return data conclude that predictability runs *from the public to private* markets. To test for reverse causality, we use *PPR* as the dependent variable in equation (1) and regress it on lagged firm-level REIT returns as well as our control variables. The results displayed in Appendix 2 reveal no ability of lagged REIT returns to predict *PPR*; more specifically, the estimated coefficients on returns, both contemporaneous and lagged one-to-four quarters, are statistically insignificant in all model specifications.

We perform robustness tests using MSA-level economic activity indices. Specifically, we control for quarterly variation in MSA-level GDP and personal income, using either all local industries or only the real estate industry (i.e., the real estate and rental and leasing sector, NAICS code 53) in a local market. Because these MSA-level macroeconomic variables (obtained from the BEA) are available beginning in 2001, we conduct this robustness analysis for a restricted sample. The results, which are summarized in Appendix 3, are largely consistent with our featured results. We also explore whether the return predictability of *PPR* is driven by a subsample of time periods. In unreported results, we augment equation (1) by interacting *PPR* with a dummy variable that is set equal to one if the observation occurs during the Great Recession (2017Q1–2019Q2, as defined by NBER). These interaction coefficients are insignificant, which suggests the return predictability of *PPR* we document is not driven by the pre- or post-crisis periods.

The evidence we have presented is consistent with a slow diffusion of information about the performance of geographically dispersed local markets into REIT stocks price. However, in the absence of clearly identifiable exogenous shocks to the information environment in local CRE markets, it is not possible to definitively rule out other channels and sources of endogeneity. For example, if *PPR*s are correlated with an omitted risk factor, the positive relation we document between *PPR* and REIT returns could be spurious.

We have demonstrated that our controls for local market liquidity (*PropTO*) and economic activity (*IEA*) do not explain REIT returns and their inclusion does not affect the positive and significant coefficient on *PPR*. To further investigate potential risk-based explanations, we examine whether the positive relation we document between *PPR* and REIT returns is driven by the correlation of *PPR* with local land supply constraints and government land use regulations associated with certain geographic locations that are omitted from our regression specifications. Saiz (2010) identifies a significant relation between land supply elasticity and property values. Relatively inelastic MSAs (e.g., New York, Los Angeles, and Miami) tend to have higher land values and increased regulations on development. Thus, increased asset concentrations in these MSAs may affect firm returns, independent of the information contained in *PPR*.

We utilize Saiz's (2010) measure of MSA-level supply elasticity, which we weight by each REIT's exposure to each MSA to produce a firm-level supply elasticity ($INELAST_{i,t}$). We then add $INELAST_{i,t}$ to our Fame-Macbeth specification and report the regression results in Column (2) of Table 7. For comparison purposes, our baseline Fama-Macbeth results are reproduced in column (1). We do not observe a positive relation between *INELAST* and firm returns; that is, firms with larger allocations to supply constrained markets MSAs do not earn greater returns than their peers. The estimated coefficient on *PPR* remains positive and significant.

We also replace Saiz's (2010) supply constraint variable with a measure of the strictness of land use regulations, as estimated by the Wharton Residential Land Use Regulatory Index (*WRLURI*) (Gyourko et al., 2008). We then construct a variable, $WRLURI_{i,t}$, that weights MSA land use regulations by each REIT's exposure to each MSA and add $WRLURI_{i,t}$ to our baseline cross-sectional regression. These results are reported in Column (3) of Table 7. The estimated coefficient on $WRLURI_{i,t}$ is not distinguishable from zero and the *PPR* coefficient remains positive and highly significant.

To provide further evidence of an information-based channel, we control for the degree of information risk in the markets in which the REIT is invested using a risk classification strategy well established in the literature: the percentage of total property value in each MSA that represents land. According to Kurlat and Stroebel (2015) and Kurlat (2016), the location attributes of a property are more difficult to value than its structural characteristics. Thus, land share is a proxy for the factor loading of property values on local market characteristics. In related work, Davis and Heathcote (2007), Bostic et al. (2007) and Bourassa et al. (2011) find that land share is strongly associated with a property's relative exposure to the local fundamentals that influence property prices. Therefore, risk and return could be corelated with the extent to which a REIT's portfolio is allocated to high land share MSAs.

Using the S&P Global Real Estate Properties database, we decompose the initial cost of each property in our database into a land (location) and structural component. We then calculate the percentage of total property value attributable to the land for each property in the year in which it was acquired. These property-level land shares in each MSA are then weighted by the initial total cost of the property to produce an average, time-invariant, land share for each MSA in our sample. We expect information risk to be greater in MSAs with higher average land shares. These MSA-level land share are then weighted by each REIT's portfolio exposure to each MSA to produce a firm-level land share exposure, $SLAND_{i,t}$. In the specification reported in column (4), the estimated coefficient on *SLAND* is insignificant and the magnitude and significance of our *PPR* coefficient is little changed by the addition of *SLAND*. Similar results are obtained using panel regressions (Columns (5)-(8)).

Overall, these tests suggest that our private predicts public results are not being driven by supply elasticity, regulatory constraints, the degree of information risk, local market liquidity, or local economic activity. Although our analysis is primarily cross-sectional in nature and we do not claim causality, these results provide strong support for a slow diffusion of information channel.

4.5 Other Potential Mechanisms that Drive the Predictability of REIT Returns

We decompose *PPR* into an income return component (*PPR_INC*) and a price appreciation component (*PPR_PRC*). Our quarterly summary statistics in Table 1 indicate that the income component represents a significant fraction of *PPR*; on average, 73% (=1.68%/2.30%) of *PPR* is derived from *PPR_INC*. Moreover, the standard deviation of the appreciation component is 3.4 times its mean, while the standard deviation of the income component is just 21% of its mean. This pattern also exists for each property type (results untabulated). 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 component is similar across public and private CRE indices and exhibits little volatility, whereas the price appreciation component varies significantly across the two markets. 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 to investors 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 *PPR* decomposed into its income and price appreciation components. The results reported in Table 8 are consistent with the price appreciation story: the coefficient estimates on *PPR_PRC* are positive and highly significant; for example, a change in *PPR_PRC* from the bottom to the top quartile is associated with an increase in quarterly *RetRf* of 0.92 percentage points in model (1). In contrast, the estimated coefficients on *PPR_INC* are statistically insignificant (model (2)). The results are consistent when we include both components in model (3). Although untabulated, similar results are obtained using annual data and panel regressions.

To further examine the channel(s) through which *PPR* affects future REIT returns, we calculate 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 for those 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). If the ability of

PPR to predict returns 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. Same-store NOI growth, *SS_NOI_Growth* has a mean of 2.40% and a standard deviation of 4.44% (Table 1).[19] This variable is available only for a smaller sample of larger REITs.[20]

The results reported in Table 9 confirm a positive and significant relationship between quarterly *PPR*s and same-store NOI growth. Importantly, only the price appreciation component (*PPR_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.

4.6 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 *PPR* to predict stock returns is driven primarily by a firm's investments in secondary and tertiary markets because less information is available about the

[19] Raw NOI Growth has a mean of 15.90% and a standard deviation of 55.47%.

[20] 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.

performance of these markets prior to the release each quarter of the disaggregated NCREIF return indices.

However, 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); thus, 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 could be 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 *PPR*s associated with allocations to gateway markets are more predictive of REIT returns than the *PPR*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.[21] 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.[22] 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. In addition to the six gateway markets, these MSAs include the following 19 MSAs: Atlanta, 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. [23]

[21] 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.

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

[23] 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

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 the 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 yearly average of these allocations across the REITs in our sample to generate a time series of average allocations to each tier. These average yearly allocations are plotted in Figure 2. At the beginning of 1996, allocations to the gateway market averaged 27%. The corresponding averages for secondary and tertiary markets we 47% and 26%, respectively. The mean allocation to gateway markets trended up over our sample period and averaged 47%. The mean allocation to secondary markets trended down and averaged 30%. Allocations to tertiary markets remained relatively stable.

Table 10 contains the firm-level statistics (means, standard deviations, and 25th, 50th, and 75th percentiles) of raw *PPR* returns for our sample. Quarterly *PPR* returns on portfolio allocations to gateway markets averaged 2.30%. The corresponding return percentages for secondary and tertiary markets are 2.23% and 2.18%, respectively. The contemporaneous time-series correlations of average *PPR*s for gateway allocations with *PPR*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 11, we report results obtained from re-estimating our baseline cross-sectional regressions (equation (1)) using, in turn, *PPR*s for each REIT's gateway, secondary, and tertiary allocations. As a reference, the results from our baseline cross-sectional regression are reported in column (1). In models (2)-(4), we observe a

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., 2019a; Wang and Zhou, 2020).

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 *PPR*s for each REIT's gateway and secondary allocations is positive and significant at the 1% and 5% level, respectively. The estimated PPR coefficient for allocations to tertiary markets cannot be distinguished from zero. In model (5), we include all three *PPR*s. The estimated *PPR* coefficients are largely unchanged.

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 *PPR* is attributable to cross-sectional variation in the diffusion of information about local property price appreciation, not variation in income returns (section 4.6).

4.7 *The Nature of Information Frictions*

One could argue that modern technology makes it possible for investors to access information such as the NCREIF indices and property holdings data we use in this study. However, frictions could delay a timely price adjustment if investors are unable to collect, assimilate, and incorporate all value-relevant information into stock prices. In this section, we test our assertion that geographic impediments to information collection, exacerbated by investors' limited attention, likely explain the ability of cross-sectional dispersion in local property market performance and REIT firms' property holdings to predict returns.

There is support for our conjecture in the literature. In particular, Coval and Moskowize (1999, 2001) and Ivkovic and Weisbenner (2005) find that investors tend to focus on local news and are unable to aggregate all value-relevant information. Cziraki et al. (2020) find that firms' stock returns are positively associated with the degree to which firms receive "asymmetric" attention from local investors. Korniotis and Kumar (2013) document a strong link between local business cycles and local stock returns because local investors tend to trade on a common local information set, which leads to correlated trading behavior that affects the prices of local stocks

(Pirinsky and Wang, 2006). Ling et al. (2019b) find that institutional investors tend to overweight REITs headquartered in the investors' home market and REITs with measurable real investments in the investors' home market, even if the firm is not headquartered there. This tendency to tilt their portfolios toward "local" assets, together with limited attention, suggests that the predictability might vary across firms depending on the local ownership.

To establish the link between investor attention and return predictability, we follow Hong, Kubik, and Stein (2008) and Korniotis and Kumer (2013) and construct two measures of visibility: firm size and a visibility index. The visibility index is defined as the residual from a regression of the log of the number of shareholders on the log of firm size. We first estimate a visibility regression for each quarter. Next, we conduct a simple sorting exercise to examine whether the ability of *PPR* to predict REIT returns is affected by firm visibility. In Panels A and B of Table 12, we sort firms by beginning period *PPR* and by our visibility proxies. For both high- and low-visibility REITs, returns are higher among the high-*PPR* group. Further, the return difference is only statistically significant among low visibility firms.

We further narrow down to the role of geography in information transmission. Although we are unable to identify the location of each investor's home market, we are able to do so for each REIT's institutional investors. With these data, we follow Ling et al. (2019b) and construct time-varying measures of each REIT's "excess" local ownership. We then divide REITs into low (below median) and high (above median) excess local ownership subsamples in each quarter. Within each subsample, we further partition REITs based on the sample median of *PPR* in that quarter. We examine the performance for the Long-Short portfolio in each subsample. We find that the returns of the Long-Short portfolio with high excess local ownership are more sensitive to changes in local market conditions, leading to stronger predictable return patterns.

5. Conclusion

In this paper, we construct a novel time-series measure of the returns on similar properties located in the MSAs in which the REIT is invested. We label these geographically-weighted returns as the REIT's property portfolio returns ("*PPRs*"). 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. This result is not driven by the liquidity or general economic activity in the local markets in which the REIT is invested. 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.

We conduct a battery of additional robustness tests. We show that innovations in *PPR* also predict REIT returns. 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 regress *PPR* on lagged firm-level REIT returns and find no "reverse" predictability. We also rule out alternative explanations for the ability of *PPR* to predict REIT returns (e.g., local supply elasticities, regulatory constraints, and the degree of local information risk) that might confound our results.

To examine the potential mechanisms that drive the predictability of returns, we decompose *PPR*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 *PPR*s and the "same-store" rental growth of REITs. This suggests that the ability of *PPR* to predict REIT returns is not driven purely by changes in the property portfolio composition of the REIT portfolio. By decomposing *PPR*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. We also provide evidence consistent with the hypothesis that our results are driven by geographic boundaries that impede the ability of investors to collect, process, and price location specific information that has affected the dividend paying ability of a REIT.

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 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.

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Figure 1: Time Trends in Property Portfolio Returns (*PPRs*)

This figure shows the time-series trends in the distribution of quarterly property portfolio return (*PPR*) for the period from 1996Q1 through 2018Q4. The circle indicates the mean of *PPR*s across individual firms, with 90% confidence intervals. The dash line shows total returns on the national NCREIF NPI index. See Appendix 1 for variable descriptions.

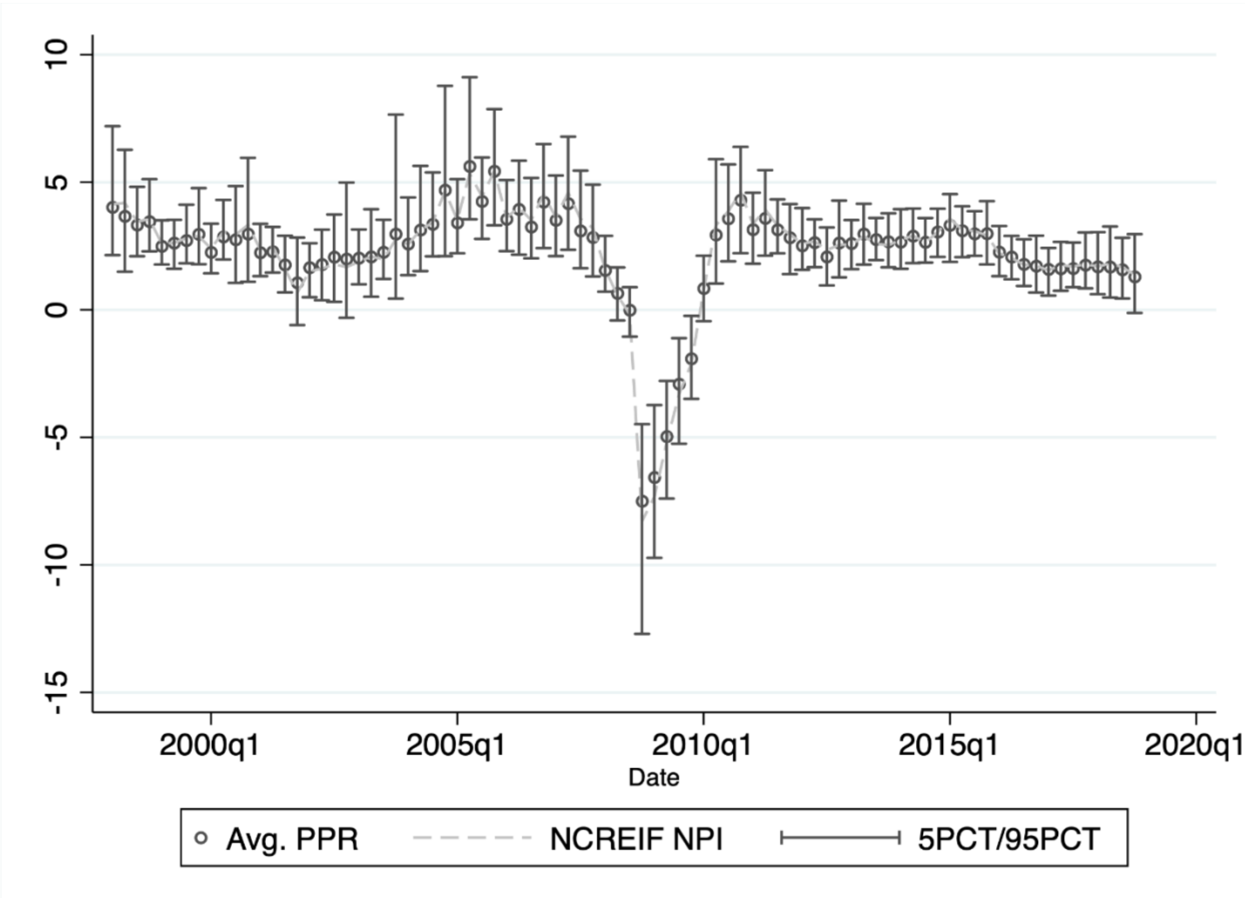

Figure 2: Gateway, secondary, and tertiary market allocations by equity REITs.

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.

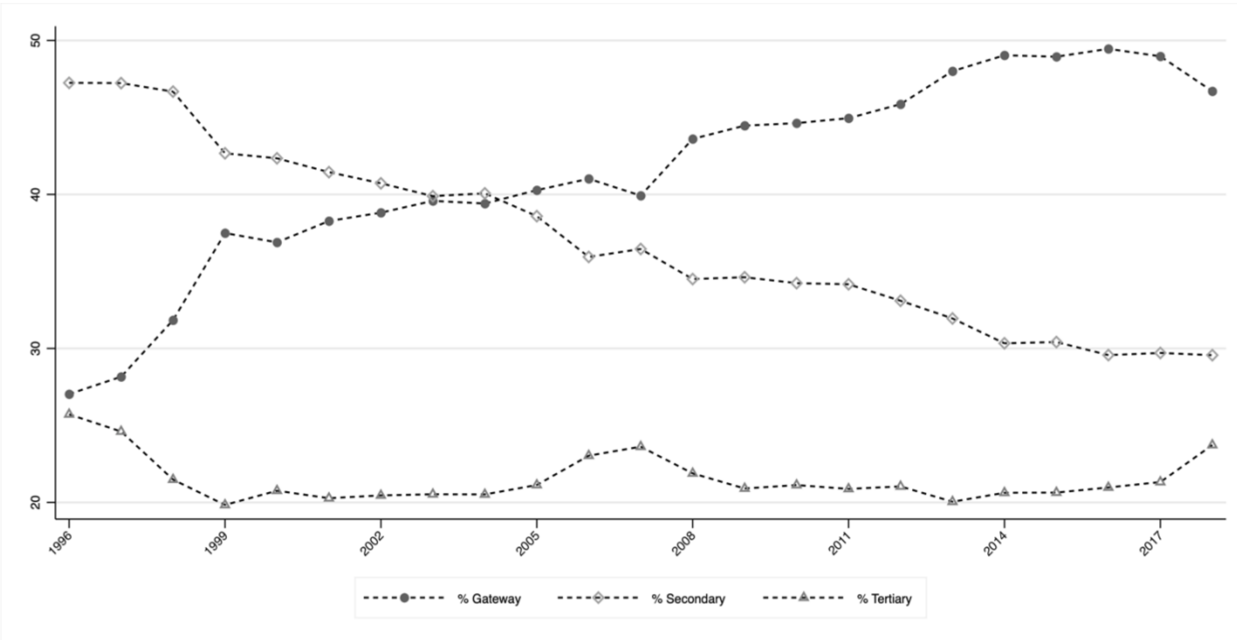

Table 1: Summary Statistics

This table shows summary statistics (number of observations, mean, standard deviation (SD), and 25th, 50th, and 75th percentiles) for a sample of 6,591 firm-quarter observations from 1996-2018. See Appendix 1 for variable descriptions.

	# 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
Property Portfolio Returns						
PPR	6,591	2.30	2.21	1.68	2.52	3.29
PPR Innovation	6,591	-0.01	1.14	-0.48	-0.01	0.56
Channels						
PPR PRC	6,591	0.61	2.10	0.04	0.77	1.61
PPR INC	6,591	1.68	0.36	1.39	1.62	2.03
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
PropTO	6,591	1.54	1.78	0.10	1.20	2.24
GMP_ALL	4,345	4.08	2.41	3.09	4.35	5.46
GMP_REL	4,345	3.55	2.75	2.08	3.47	5.01
INC_ALL	4,345	4.25	2.91	2.76	4.86	6.25
INC_REL	4,345	1.15	0.50	0.85	1.13	1.40
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

Table 2: Sorts on Property Portfolio Returns (*PPRs*)

This table shows average REIT returns for sorts on quarterly *PPR* (Panel A) and annual *PPR* (Panel B) 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*. 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 *PPRs* 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.

Panel A: Quarterly *PPR*

	(1)		(2)		(3)		(3)-(1)	t-stat	z-stat
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: Annual *PPR*

	(1)		(2)		(3)		(3)-(1)	t-stat	z-stat
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***

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 Columns (1)-(3), and (4)-(6), respectively. Results are based on quarterly sample of 6,591 firm-quarter observations from 1996-2018. The quarterly REIT returns (*RetRf (Qtr)*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *PPR (Lag1)* is the property portfolio returns of firm *i* in quarter *t-1*. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
RetRf (Qtr)	FM	FM	FM	Panel	Panel	Panel
PPR (Lag 1)		0.695***	0.620***		0.668***	0.654***
		(3.33)	(3.25)		(3.95)	(3.86)
PropTO			-2.945			0.248
			(-1.26)			(1.44)
IEA		0.427	0.678		0.243	0.242
		(0.95)	(1.47)		(0.55)	(0.54)
Size	-0.121	-0.166	-0.184	-4.014***	-3.980***	-3.976***
	(-0.69)	(-0.96)	(-1.10)	(-6.19)	(-6.14)	(-6.14)
B/M	1.217	1.329	1.291	5.692**	5.691**	5.700**
	(1.51)	(1.56)	(1.48)	(2.44)	(2.43)	(2.43)
Momentum	0.048***	0.043***	0.043***	0.043***	0.040***	0.040***
	(3.81)	(3.32)	(3.35)	(4.30)	(3.92)	(3.94)
Leverage	-0.046	-0.445	-0.331	-1.145	-1.191	-1.241
	(-0.03)	(-0.30)	(-0.21)	(-0.45)	(-0.47)	(-0.49)
Profitability	0.160***	0.160***	0.158***	0.089***	0.089***	0.090***
	(3.75)	(4.01)	(3.99)	(3.01)	(3.01)	(3.00)
Investment	0.030	0.024	0.026	0.003	0.002	0.002
	(0.80)	(0.60)	(0.57)	(0.25)	(0.19)	(0.19)
ILLIQ	-2.998	-4.195	-4.426	-2.280*	-2.314*	-2.287*
	(-0.52)	(-0.69)	(-0.68)	(-1.69)	(-1.72)	(-1.69)
IVOL	-1.396*	-1.325	-1.343*	-1.563***	-1.553***	-1.556***
	(-1.79)	(-1.65)	(-1.68)	(-2.86)	(-2.84)	(-2.84)
Constant	3.082	1.069	1.072	27.382***	24.996***	24.691***
	(1.40)	(0.43)	(0.44)	(4.47)	(4.03)	(3.98)
Prop FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes	Yes
R-squared	0.354	0.384	0.398	0.539	0.541	0.541
# Obs	6,591	6,591	6,591	6,591	6,591	6,591

Table 4: Long-Horizon Predictability of Property Portfolio Returns

This table reports *h*-period-ahead return predictability of *PPR*. Fama-MacBeth results based on quarterly datasets. The quarterly REIT returns (*RetRf (Qtr)*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *PPR (Lag r Qtr)* is the property portfolio returns of firm *i* in quarter *t-r*. See Appendix 1 for variable descriptions. Control variables are the same as in columns (1)-(3) of 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)
PPR (Lag 1 Qtr)	0.674***				
	(3.55)				
PPR (Lag 2 Qtr)		0.872***			
		(3.67)			
PPR (Lag 3 Qtr)			0.495**		
			(2.27)		
PPR (Lag 4 Qtr)				0.674***	
				(2.73)	
PPR (Lag 5 Qtr)					0.409**
					(2.10)
PropTO	-1.384	-1.225	-1.793	-1.844	-1.836
	(-1.01)	(-0.94)	(-1.18)	(-1.30)	(-1.13)
IEA	0.693	0.634	0.669	0.562	0.735
	(1.40)	(1.19)	(1.29)	(1.02)	(1.50)
Controls	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes
R-squared	0.402	0.404	0.406	0.402	0.404
# Obs	6,416	6,416	6,416	6,416	6,416

Table 5: Regression Results of Excess Returns on Property Portfolio Return Innovations

This table shows the regression results on the relationship between REIT excess returns and property portfolio return (PPR) innovation. Results based on Fama-MacBeth (1973) and panel regression analysis are presented in Columns (1)-(2), and (3)-(4), respectively. The quarterly REIT returns (*RetRf (Qtr)*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *PPR (Lag 1)* is the property portfolio returns of firm *i* in quarter *t-1*. *PPR Innovation is* PPR orthogonalized with respect to lagged PPRs over the past four quarters. 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 Fama-MacBeth regressions. Firm and time fixed effects are included in the panel regressions. 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)
	FM	FM	Panel	Panel
PPR (Lag 1)	0.620***		0.654***	
	(3.25)		(3.86)	
PPR Innovation (Lag 1)		0.856***		0.334**
		(3.02)		(2.14)
PropTO	-2.945	-2.714	0.248	0.201*
	(-1.26)	(-1.12)	(1.44)	(1.71)
IEA	0.678	0.563	0.242	0.220
	(1.47)	(1.02)	(0.54)	(0.59)
Controls	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	No	No
FirmFE	No	No	Yes	Yes
TimeFE	No	No	Yes	Yes
R-squared	0.398	0.398	0.541	0.540
# Obs	6,591	6,591	6,591	6,591

Table 6: 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 (Qtr)* is the quarterly unlevered returns of firm *i* in quarter *t*, calculated using the Ling and Naranjo (2015) method. *PPR (Lag 1)* is the property portfolio returns of firm *i* in quarter *t-1*. 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) and (2). Firm and time fixed effects are included in panel regressions in Columns (3) and (4). 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)
UnlevRet (Qtr)	FM	FM	Panel	Panel
PPR (Lag 1)	0.231**	0.215**	0.282***	0.280***
	(2.62)	(2.48)	(3.86)	(3.86)
PropTO		-1.481		0.037
		(-1.39)		(0.88)
IEA	0.456*	0.486**	-0.071	-0.070
	(1.94)	(2.15)	(-0.42)	(-0.42)
Controls	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	No	No
FirmFE	No	No	Yes	Yes
TimeFE	No	No	Yes	Yes
R-squared	0.314	0.330	0.534	0.534
# Obs	5,882	5,882	5,882	5,882

Table 7: Supply Elasticity, Information Environment, and the Predictability of Property Portfolio Returns

This table shows the regression results on the relationship between REIT excess returns and property portfolio return (PPR), controlling for supply elasticity or information environment. Results based on Fama-MacBeth (1973) and panel regression analysis are presented in Columns (1)-(4), and (5)-(6), respectively. The quarterly REIT returns (*RetRf (Qtr)*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *PPR (Lag 1)* is the property portfolio returns of firm *i* in quarter *t-1*. *Supply Elasticity (Saiz)* is the MSA-level supply elasticity by Saiz (2010) weighted by REIT property portfolio. *WRLURI* is the MSA-level the Wharton Residential Land Use Regulation Index (Gyourko et al., 2008), weighted by REIT property portfolio. *SLAND* is the geographically weighted MSA-level land share in Kurlat and Stroebel (2015). 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 Fama-MacBeth regressions. Firm and time fixed effects are included in the panel regressions. 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)	(6)	(7)	(8)
	FM	FM	FM	FM	Panel	Panel	Panel	Panel
PPR (Lag 1)	0.620***	0.532**	0.597***	0.614***	0.654***	0.654***	0.652***	0.654***
	(3.25)	(2.56)	(3.05)	(3.32)	(3.86)	(3.86)	(3.87)	(3.86)
Supply Elasticity (Saiz)		-0.331				0.219		
		(-1.00)				(0.43)		
WRLURI			-0.011				0.238	
			(-0.03)				(0.25)	
SLAND				-0.005				0.250
				(-0.48)				(1.45)
PropTO	-2.945	-2.928	-3.135	-2.830	0.248	0.248	0.248	0.250
	(-1.26)	(-1.44)	(-1.34)	(-1.23)	(1.44)	(1.44)	(1.44)	(1.45)
IEA	0.678	0.690	0.551	0.746	0.242	0.244	0.244	0.264
	(1.47)	(1.56)	(1.20)	(1.61)	(0.54)	(0.55)	(0.55)	(0.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	No	No	No	No
FirmFE	No	No	No	No	Yes	Yes	Yes	Yes
TimeFE	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.398	0.414	0.409	0.411	0.541	0.541	0.541	0.541
# Obs	6,591	6,591	6,591	6,591	6,591	6,591	6,591	6,591

Table 8: 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 returns. The quarterly REIT returns (*RetRf (Qtr)*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *PPR PRC (Lag 1)* is the property portfolio appreciation returns of firm *i* in quarter *t-1*. *PPR INC (Lag 1)* is the property portfolio income returns of firm *i* in quarter *t-1*. See Appendix 1 for variable descriptions. Control variables are the same as in columns (1)-(3) of 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)
RetRf (Qtr)	QTR	QTR	QTR
PPR PRC (Lag 1)	0.585***		0.515***
	(2.98)		(2.74)
PPR INC (Lag 1)		0.398	1.028
		(0.38)	(0.97)
PropTO	-2.958	-3.047	-2.631
	(-1.23)	(-1.46)	(-1.24)
IEA	0.539	1.245***	0.905*
	(1.08)	(2.75)	(1.94)
Controls	Yes	Yes	Yes
PropFE	Yes	Yes	Yes
R-squared	0.399	0.401	0.416
# Obs	6,591	6,591	6,591

Table 9: 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 *PPR*. The dependent variable, *SS NOI Growth (Qtr)*, is the percentage change in net operating income from the previous quarter on properties owned for the entire current quarter and in the entire previous quarter. *PPR PRC (Lag1)* is the property portfolio appreciation returns of firm *i* in quarter *t-1*. *PPR INC (Lag1)* is the property portfolio income returns of firm *i* in quarter *t-1*. See Appendix 1 for variable descriptions. Control variables are the same as in columns (1)-(3) of 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.

SS NOI Growth (Qtr)	(1)	(2)
PPR (Lag 1)	0.276***	
	(4.91)	
PPR PRC (Lag 1)		0.274***
		(3.79)
PPR INC (Lag 1)		0.376
		(0.22)
PropTO	0.015	0.015
	(0.34)	(0.35)
IEA	0.512**	0.511***
	(2.56)	(2.81)
Controls	Yes	Yes
PropFE	Yes	Yes
R-squared	0.528	0.528
# Obs	3,869	3,869

Table 10: 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)	2.30	2.13	1.71	2.51	3.25
PPR (Secondary)	2.23	2.06	1.65	2.29	3.13
PPR (Tertiary)	2.18	2.31	1.58	2.29	3.14

Table 11: 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 quarterly REIT returns (*RetRf (Qtr)*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *PPR (Lag 1)* is the property portfolio returns of firm *i* in quarter *t-1*. See Appendix 1 for variable descriptions. Control variables are the same as in columns (1)-(3) of 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)
PPR (Lag 1)	0.620***				
	(3.25)				
PPR (Gateway)		0.470***			0.465***
		(4.13)			(4.26)
PPR (Secondary)			0.377**		0.351**
			(2.24)		(2.16)
PPR (Tertiary)				0.117	0.047
				(0.92)	(0.36)
PropTO	-2.945	-3.061	-2.905	-3.333	-2.892
	(-1.26)	(-1.28)	(-1.45)	(-1.42)	(-1.45)
IEA	0.678	0.498	0.866*	0.811*	0.661
	(1.47)	(1.03)	(1.68)	(1.74)	(1.40)
Controls	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes
R-squared	0.398	0.401	0.395	0.396	0.424
# Obs	6,591	6,591	6,591	6,591	6,591

Table 12: Information Frictions

This table shows average annual REIT returns for sorts on PPR and firm size in Panel A, on PPR and investor visibility in Panel B, and on PPR and excess local institutional ownership in Panel C. Investor visibility index is defined as the residual from a regression of the log of the number of shareholders on the log of firm size (Hong, Kubik, and Stein, 2008). Excess local institutional ownership (*Excess Local Own*) is MSA-level ownership of firm *i*, calculated as aggregate ownership share of institutional investors headquartered in MSA *l* as a fraction of total institutional ownership share in firm *i* in quarter *t*, minus the average ownership share of institutions in MSA *l* across all REITs in quarter *t* (Ling, Wang, and Zhou, 2019). In Panel A, Large (Small) group consists of the set of REITs with firm size above (below) the sample median in period t. Within each size group, we further sort REITs into two portfolios based on their PPR in quarter t, and compute average REIT returns for quarter t+1. Panels B and C follow the same sorting strategy. The REIT returns are measured by the chain-linked monthly excess returns. The reported statistics in Columns (1) and (2) are equally weighted averages across all REITs in each of the four subgroups. Column (3) reports the return differences between columns (1) and (2). Test statistics are reported in the last two columns. See Appendix 1 for variable descriptions.

Panel A: Firm Size

	(1) High *PPR*	(2) Low *PPR*	(3) Difference	(4) *t*-test	(5) rank sum
Large	1.78	1.25	0.53	1.90*	3.17***
Small	2.92	1.85	1.07	3.32***	3.78***

Panel B: Investor Visibility

	(1) High *PPR*	(2) Low *PPR*	(3) Difference	(4) *t*-test	(5) rank sum
High Visibility	2.27	1.76	0.51	1.85*	2.27**
Low Visibility	2.39	1.38	1.01	3.06***	4.25***

Panel C: Excess Local Institutional Ownership

	(1) High *PPR*	(2) Low *PPR*	(3) Difference	(4) *t*-test	(5) rank sum
High Excess Local Own	1.98	0.36	1.63	4.72***	5.93***
Low Excess Local Own	2.51	1.81	0.70	0.95	2.68**

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.
Property Portfolio Returns		
$PPR_{i,t}$	NCREIF, S&P Global	The 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.
$PPR\ Innovation_{i,t}$	NCREIF, S&P Global	PPR orthogonalized with respect to lagged PPRs over the past four quarters.
Channels		
$PPR\ PRC_{i,t}$	NCREIF, S&P Global	The property portfolio appreciation returns of firm *i* in period *t*, calculated as the appreciation component of NCREIF NPI property-MSA sub-indices, weighted by the percentage of the REIT's portfolio allocated to each property type in each MSA.
$PPR\ INC_{i,t}$	NCREIF, S&P Global	The property portfolio income returns of firm *i* in period *t*, calculated as the income component of NCREIF NPI property-MSA sub-indices, weighted by the percentage of the REIT's portfolio allocated to each property type in each MSA.

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.
Visibility$_{i,t}$	Compustat	The residual from a regression of the log of the number of shareholders on the log of firm size.
Excess local ownership$_{i,t}$	Thomson Reuters, SEC	The firm-level average of MSA-level ownership percentages of firm *i*. MSA-level excess ownership is calculated as aggregate ownership share of institutional investors headquartered in MSA *l* as a fraction of total institutional ownership share in firm *i* in quarter *t*, minus the aggregate ownership share of institutions in MSA *l* across all firms in quarter *t*.
Control Variables		
IEA$_{i,t}$	Federal Reserve	The orthogonalized regional economic activity indices, calculated using the Smajlbegovic (2019) method.
GMP_ALL$_{i,t}$	BEA	Annual change in real gross domestic product for all industry total by Metropolitan Statistical Area.
GMP_REL$_{i,}$	BEA	Annual change in real gross domestic product for real estate and rental and leasing by Metropolitan Statistical Area.
INC_ALL$_{i,t}$	BEA	Annual change in personal income for all industry total by Metropolitan Statistical Area.
INC_REL$_{i,t}$	BEA	Annual change in personal income for real estate and rental and leasing by Metropolitan Statistical Area.
PropTO$_{i,t}$	NCREIF	The average of MSA-level property market turnover, weighted by REIT allocation to each MSA
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		Property type focus of the REIT in Fama–MacBeth cross-sectional regressions or firm fixed effects in panel regressions.
θ_t		Time (year or year-quarter) fixed effects.
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 and Lead Predictability

Panel A shows Fama-MacBeth (1973) regression results on the relationship between property portfolio returns and REIT excess returns. *PPR (Qtr)* is the property portfolio returns of firm *i* in quarter *t*. The quarterly REIT returns (*RetRf*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *RetRf* (*Contemp*) is contemporaneous *RetRf*. *RetRf (Lag r)* is *RetRf* lagged by *r* quarter(s). Panel B reports *h*-period-ahead return predictability of *PPR*. Fama-MacBeth results based on quarterly datasets. The quarterly REIT returns (*RetRf (Qtr)*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *PPR (Lag r Qtr)* is the property portfolio returns of firm *i* in quarter *t-r*. *PPR (Contemporaneous)* is the property portfolio returns of firm *i* in quarter *t*. *PPR (Lead r Qtr)* is the property portfolio returns of firm *i* in quarter *t+r*. See Appendix 1 for variable descriptions. Control variables are the same as in columns (1)-(3) of 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.

Panel A: Reverse Causation

PPR (Qtr)	(1)	(2)	(3)	(4)	(5)
RetRf (Contemp)	0.001				
	(0.69)				
RetRf (Lag 1)		-0.001			
		(-0.24)			
RetRf (Lag 2)			-0.004		
			(-1.56)		
RetRf (Lag 3)				0.002	
				(0.90)	
RetRf (Lag 4)					0.000
					(0.20)
PropTO	0.160	0.268	0.245	0.187	0.219
	(0.89)	(1.28)	(1.17)	(1.02)	(1.11)
IEA	0.302***	0.338***	0.347***	0.332***	0.354***
	(2.72)	(2.64)	(2.69)	(2.75)	(2.79)
Controls	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes
R-squared	0.361	0.358	0.361	0.358	0.361
# Obs	6,591	6,591	6,591	6,591	6,591

Panel B: Lead Predictability

RetRf (Qtr)	(1)	(2)	(3)	(4)	(5)	(6)
PPR (Lag 1 Qtr)	0.428**					
	(2.37)					
PPR (Contemp)		0.112				
		(0.86)				
PPR (Lead 1 Qtr)			0.166			
			(0.98)			
PPR (Lead 2 Qtr)				0.307		
				(1.60)		
PPR (Lead 3 Qtr)					0.063	
					(0.26)	
PPR (Lead 4 Qtr)						0.057
						(0.21)
PropTO	0.468	1.126	-0.665	0.056	0.155	0.111
	(0.31)	(0.72)	(-0.42)	(0.03)	(0.10)	(0.06)
IEA	0.727	1.080	0.665	0.966	0.407	0.767
	(0.98)	(1.42)	(0.95)	(1.47)	(0.54)	(1.16)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.501	0.504	0.504	0.501	0.501	0.505
# Obs	5,921	5,921	5,921	5,921	5,921	5,921

Appendix 3: Robustness Tests using MSA-level Economic Activity Index

This appendix summarizes Fama-MacBeth (1973) regression results using MSA-level economic activity indices. The quarterly REIT returns (*RetRf (Qtr)*) are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 30-day Treasury bills. *PPR (Lag 1)* is the property portfolio returns of firm *i* in quarter *t-1*. *PPR Innovation is* PPR orthogonalized with respect to lagged PPRs over the past four quarters. GMP (All Industry) is MSA-level gross domestic product in all industries. GMP (RE & Leasing) is MSA-level gross domestic product in real estate and leasing. INC (All Industry) is MSA-level personal income in all industries. INC (RE & Leasing) is MSA-level personal income in real estate and leasing. 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)	(2)	(3)	(4)	(5)	(6)
PPR (Lag 1)	0.620***	0.864***	0.823***			
	(3.25)	(3.19)	(3.22)			
PPR Innovation (Lag 1)				0.856***	0.846**	0.727*
				(3.02)	(2.31)	(1.98)
PropTO	-2.945	-0.193	-0.141	-2.714	-0.136	-0.133
	(-1.26)	(-0.57)	(-0.38)	(-1.12)	(-0.44)	(-0.35)
IEA	0.678			0.563		
	(1.47)			(1.02)		
GMP (All Industry)		-0.263			-0.400*	
		(-1.27)			(-1.73)	
INC (All Industry)		0.224			0.348	
		(0.98)			(1.53)	
GMP (RE & Leasing)			-0.071			-0.062
			(-1.10)			(-0.96)
INC (RE & Leasing)			0.178			0.092
			(0.40)			(0.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PropFE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.398	0.410	0.400	0.398	0.405	0.395
# Obs	4,355	4,355	4,355	4,355	4,355	4,355