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Title: Local Beta: Have Location Risks Been Priced in REIT Returns?

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Abstract

This paper studies the pricing of the risk associated with the location of the assets. The location risk is measured by 'local beta', which combines the systematic risk of local property markets and the property allocation strategy of real estate firms. The empirical results confirm a higher equity return for a firm with higher exposure to the most volatile property markets, particularly for REITs which are more geographically concentrated. For REITs with highly diversified assets, location risks are reflected in REIT returns. For those REITs with most concentrated assets, a one standard deviation increase in the local beta will lead to a 4.5% increase in the annual return. Investors can use REITs' location risk as an information tool to construct a long-short investment portfolio of real estate firms and can achieve a significant non-market performance of 6% per annum.

Keywords: Geographic asset location, real estate returns, location risks, diversification.

JEL Classification: G12, R3

1 Introduction

The importance of location on property investment has been highlighted in the literature. However, the location factor has not been well incorporated into the asset pricing of REIT equities. One reason could be that many REITs have a diversified property portfolio, making it difficult to identify local factors for REITs. Different measures have been employed in the previous literature. Some literature focuses on the ‘quality’ of the location. For example, Ling et al. (2018a) find a significant positive impact on REITs’ returns stemming from the exposure to the so-called ‘Gateway’ markets. Other literature investigates the distance of properties from the headquarters of the firm. In line with the home bias theory, Ling et al. (2018b) find a significant positive relationship between home market concentration and firm returns. Consistent with managerial alignment theory, Wang et al. (2017) find that REITs tend to dispose of distant properties and that there is a negative relationship between distance and cumulative abnormal return. Based on information asymmetry theory, Conklin et al. (2018) show that the location of a property relative to a REIT's main business location can affect the financing of that property. The third strand of literature uses spatial econometric approaches to quantify the impact of the local factor. The idea is that, if the location of the assets affects REIT performance, REITs with more geographically-overlapping assets should exhibit stronger co-movements in their equity returns. Using an unbalanced spatial panel model, Zhu and Milcheva (2018) find evidence to support this argument. A fourth strand of literature investigates the risks associated with geographically-determined natural disasters. For instance, Rehse et al. (2019) find relatively less trading and wider bid-ask spreads in REITs who were affected by Hurricane Sandy, confirming the effects of uncertainty on market liquidity.

This paper uses a more direct measurement – local beta – to measure the economic riskiness of local markets. Local beta is the sensitivity of the local property market to any aggregate shocks. It reflects on the systemic risk and cyclicality of the local property market. This paper studies the impact of local beta on REIT equity returns. By doing so, this study can contribute to general asset pricing literature concerning geographical immobility. Tuzel and Zhang (2017) propose two mechanisms by which the local factor can affect a firm’s value – wages and rental rates – because both labour markets and property markets are segmented. The two channels are competing. On the one hand, in regions more sensitive to aggregate shocks, employees should require higher wages.

From the firms' perspective, more cyclical wages absorb part of the aggregate shocks. This provides a natural hedge for firms in high beta areas and lowers their risk relative to industry peers located in low beta areas. On the other hand, real estate values respond more strongly to aggregate shocks in high beta areas than in low beta areas. As firm value is derived, in part, from the value of its capital, including corporate real estate, one can expect a higher risk for firms in high beta areas than for firms in low beta areas. By investigating all U.S. firms, Tuzel and Zhang (2017) find evidence to support the wage hedging mechanism. They also show that the effect is stronger for firms with lower real estate holdings. This paper focuses on REITs, which are more likely to be influenced by the second mechanism. The results of this paper confirm a significant premium for location risks for REITs. For robustness, issues regarding self-selection, valuation smoothing, and leverage are addressed: this conclusion remains supported. This paper can, therefore, provide empirical evidence for the second channel – the real estate channel.

Given that the REIT structure typically provides investors with access to skilled property managers with diversified property holdings, investors may assume that idiosyncratic events in individual local areas are less likely to influence the overall performance of REITs. In this paper, we also investigate whether geographic diversification can successfully remove the location risk for REITs. In doing so, our results can also shed light on the diversification literature by providing further explanations on the relationship between diversification and stock returns. If the real estate channel matters, a higher location risk should lead to a higher equity return, due to investors' higher perceived risk. One of the purposes of geographic diversification is to hedge the cyclicality of local markets, which would imply a lower location risk for REITs with more geographically diversified assets. Therefore, one might expect lower equity returns, due to reduced location risks and thereby reduced equity risk – assuming that investors can identify that risk.

Prior literature has tried to understand the benefits/costs of diversification from management costs (Capozza and Seguin, 1998, Capozza and Seguin, 1999, Hartzell et al., 2014), information asymmetry (Ling et al., 2018b), investor's recognition (Garcia and Norli, 2012) and management alignment (Wang et al., 2017). WE add to this literature in showing that diversification affects firms' return by reducing the perceived risks of equity holdings. The empirical results confirm that location risk decreases significantly with diversification. Using the REIT data from 1998 to 2015, this paper shows that when REITs invest over 13 or more metropolitan statistical areas (MSAs), REIT equity returns should not be significantly affected by location risks[1].

Last but not least, this project also provides new evidence on the question: do listed real estate firms behave more like direct real estate or general stocks? Although this topic has been intensively studied, nearly all prior literature has focused on the time variation in the aggregated risk and return of the real estate, stock and REIT investments. For instance, many studies compared the long-term and/or short term co-movement between real estate, stock and REIT returns (see, e.g. (Morawski et al., 2008, Oikarinen et al., 2011, Glascock et al., 2000, Simon and Ng, 2009, Pagliari et al., 2005, Serrano and Hoesli, 2010, Westerheide, 2006, Sing et al., 2006, Schätz and Sebastian, 2011). Others have investigated the pricing of real estate and stock risks (Kroencke et al., 2018, Anderson et al., 2005). However, nearly all studies used aggregated index returns. Due to the fact that property markets are more segmented, with different cyclical patterns, it may not be enough to use nationwide real estate indices to proxy the performance of heterogeneous direct real estate markets. For instance, Gyourko and Nelling (1996) show that the systematic risk of equity REITs varies by the type of property and the economic regions in which the property locates. This paper studies the pricing of real estate and stock market risks, taking into account the heterogeneity in the direct real estate markets. The empirical results show that REIT equity returns are generally more sensitive to stock market risk, consistent with the previous literature. A one standard deviation increase in the local beta will result in a 1.4% increase in REIT equity returns, while a one standard deviation increase in stock beta is associated with a 2.1% increase in REIT equity returns. However, extending prior work, this study finds that the sensitivity to local real estate market risk varies across REITs according to their spatial diversification strategy. For REITs with the most concentrated assets, a one standard deviation increase in the local beta will result in an up to 5.4% increase in REIT equity returns, which is higher than the impact of stock market risk.

We proceed as follows: Section 2 summarizes the literature review. Section 3 describes our data and discussed the methodology used, Section 4 describes the findings and Section 5 concludes.

[1] We note that investors can, of course, diversify their *equity* holdings by building diversified portfolios of REITs, assuming they can identify the spatial risks they face. This will diversify idiosyncratic spatial risks, but not those that relate to systematic spatial factors that might not otherwise be captured in factor models. Further, passive investment strategies, such as an index tracking approach, could result in concentration of spatial risk.

2 Literature Review

This paper is closely related to a large and rapidly growing literature on how economic decision making is influenced by firms' geographic location. In the finance literature, work in this vein mostly concentrates on the location of the firm's headquarters (Bernile et al., 2015, Becker et al., 2011, Hong et al., 2008, Pirinsky and Wang, 2006, Tuzel and Zhang, 2017); some studies are about the location of assets related to the firm (Garcia and Norli, 2012). For example, using U.S. company data from 1993 to 2002, Pirinsky and Wang (2006) document strong co-movement in the stock returns of firms headquartered in the same geographic area. The local co-movement of stock returns is not explained by economic fundamentals and is stronger for smaller firms with more individual investors. Price formation in equity markets has a significant geographic component linked to the trading patterns of local residents. Coval and Moskowitz (2001) argue that geographic proximity matters, as local fund managers can access local information more easily and monitor the operations of local companies. Hong et al. (2008) identify a word-of-mouth channel, which means that fund managers in the same location can have correlated strategies. The limitation of using headquarters location as a proxy for the geographical distribution of the firm's operating activities has been recognised by recent papers. Fu and Gupta-Mukherjee (2014) argue that in financial markets which are characterised by large frictions in the dissemination of information, market participants can acquire information through informal channels such as the links between funds and the links between funds and companies. Garcia and Norli (2012) study the geographic dispersion of the firm's operations by counting the number of state names from annual reports filed with the SEC on Form 10-K. They find that the stock returns of truly local firms far exceed the stock returns of geographically-dispersed firms, and the premium for being local is due to the lower investor recognition for local firms, resulting in higher stock returns to compensate investors for insufficient diversification.

The impact of location on underlying assets has been more widely studied in the real estate literature[2]. The trade-off between the benefits and costs of being local has been extensively discussed. There was an early focus on management costs. For instance, (Capozza and Seguin,

[2] See, e.g., Gyourko and Nelling (1996), Capozza and Seguin (1998), Ambrose et al. (2000), Hartzell et al. (2014), Ling et al. (2018a) and many others.

1998, Capozza and Seguin, 1999), show that allocating properties in different regions may result in higher administrative costs and a higher liquidity premium that offset the benefits of diversification. More recent literature shows that there is an information advantage of being local. Ling et al. (2018b) document that managers tend to overweight asset allocations to their local market to exploit their perceived information advantage. There is a significant positive relation between home market concentrations and firm returns. However, Wang et al. (2017) find a consistently negative relationship between the distance from headquarters and cumulative abnormal returns (CARs), confirming the management alignment theory: proximity between the headquarter and underlying properties is associated with poor shareholder protection due to better employee protection. In particular, for headquarters in less-populated MSAs, the managerial alignment effect dominates the information asymmetry effect.

Very few studies focus on the riskiness of local markets and their impact on stock returns. Using the headquarters as the proxy of location, Tuzel and Zhang (2017) show that the firm location of headquarters affects firm risk through local factor prices via pro-cyclical wages, which provide a natural hedge against aggregate shocks and reduce firm risk. So firms located in higher local beta areas have lower industry-adjusted returns and conditional betas, with the effect stronger among firms with low real estate holdings. Tuzel and Zhang (2017) also addressed the limitation of using headquarters as the proxy of a firm's business locations. However, there is still a gap in the literature regarding the location of underlying assets and the location risks to which the firm is exposed. REITs provide us with an ideal sample, as the underlying assets of REITs are clearly associated with a single and identifiable location.. Gyourko and Nelling (1996) show that the systematic risk of equity REITs varies by the type of property and the economic regions in which the property locates. However, they did not identify the channel of the difference.

3 Data

3.1 Local Beta

Local beta ($\beta_{firm,t}^{local}$) is the key explanatory variable in this paper. It measures the location risks for real estate firms. A REIT with most of its properties located in very volatile real estate markets would be expected to take more real estate risks than other REITs focusing on less risky markets. Based on the property portfolio of each firm, we calculate the average systematic risk of all local markets where the firms' properties are located:

$$\beta_{i,t}^{local} = \sum_{m=1}^{M} w_{m.i,t}\beta_m, \quad (1)$$

where β_m is the MSA beta, and $w_{m.i,t}$ represents the share of properties of firm *i* in each market at period *t*. $w_{m.i,t}$ is calculated as the number of properties located in MSA *m* to total properties[3] and the location data of REIT property portfolio are extracted from the SNL database. For instance, if REIT A has 80% of properties located in the New York MSA and 20% of properties located in Miami, $\beta_{i,t}^{local}$ for REIT A will be calculated as $\beta_{i,t}^{local} = \sum_{m=1}^{2} w_{m.i,t}\beta_m = 80\% * \beta_{NY} + 20\% * \beta_{MIAMI}$. It should be noted that although β_m is constant over time, $\beta_{i,t}^{local}$ may change given the change in the REIT's property portfolio constitution.

β_m reflects the sensitivity of local commercial real estate prices in each MSA to any systematic real estate shocks, and it is calculated as[4]:

$$r_{m,q}^{NPI} - r_{f,q} = \alpha_m + \beta_m(MKT_q^{NPI} - r_{f,q}) + \varepsilon_{m,q}, \quad (2)$$

where $r_{m,q}^{NPI}$ is the direct real estate returns in market *m* in quarter *q*. We collect National Council of Real Estate Investment Fiduciaries' (NCREIF) non-profit institution (NPI) total returns for commercial real estate in 144 Core based statistical area (CBSA) and Metropolitan statistical area

[3] Alternatively, the share can also be calculated using property size or adjusted cost. Adjusted cost is as the maximum of (1) the reported book value, (2) the initial cost of the property, or (3) the historic cost of the property including capital expenditures and tax depreciation (Ling et al., 2018a). As shown in Table 3, size weighted or adjusted cost weighted real estate market illiquidity exposure generates very robust results.

[4] Instead of market aggregate NCREIF return, we also use GDP return as a measure for the systematic return. As discussed in the robustness test section: the results remain robust.

(MSA) divisions since 1978.[5] Those MSAs with return data for less than 10 quarters are excluded. However, there is a mismatch in the regions used in the two databases. SNL only records the MSA of each property, but NCREIF divides markets into CBSA and MSA divisions. Accordingly, we convert the local beta from MSA divisions to MSAs by calculating the MSA average local beta weighted by the number of NCREIF properties in each MSA division. As shown in Table 1, on average, direct real estate investments have an annual return of 8% and a standard deviation of 6%. Compared to REIT returns, the reported returns of direct real estate investments are very stable with much lower volatility[6]. $r_{f,q}$ is the risk-free rate as measured by the yield on the 1-month Treasury bill. MKT_q^{NPI} is aggregate NCREIF direct real estate returns in period q.

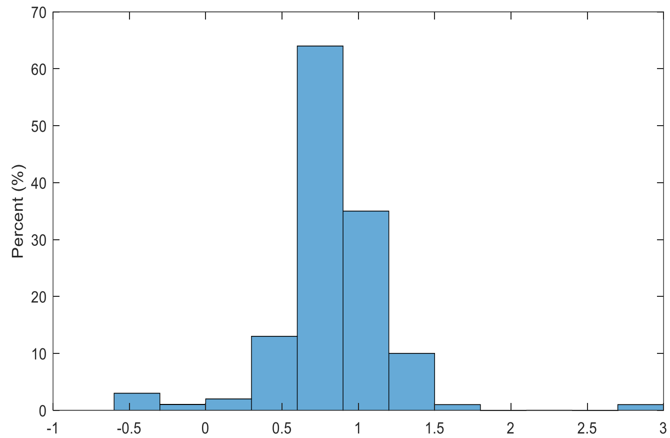
The summary statistics of the estimated β_m are reported in Table 2. β_m has a mean of 0.818 and a standard deviation of 0.379. Figure 1-1 plots the histogram of MSA betas. Most MSA betas are between 0.5 and 1.5. Albany–Schenectady Troy, NY, experienced the highest beta, over 2.5, which implies that the property markets there are very sensitive to aggregate real estate shocks. New York–Newark–Edison has the second-highest beta, close to 1.5. Three MSAs, Scranton–Wilkes–Barre, PA, Kansas City, MO-KS and Grand Rapids–Wyoming, MI, show a significant negative beta, over –0.5. This implies that the real estate market there moves in the opposite direction from the national real estate market and therefore can counter-balance the national market. The geographic distribution of MSA betas is illustrated in Figure 1-2. The strength of the betas is represented by the colour and the size of the dots. The red dot denotes a beta higher than 2, the yellow dot denotes an MSA beta between 1 and 2, the green dot denotes an MSA beta between 0 and 1 and the blue dot denotes an MSA beta less than 0. The size of the dots is proportional to the absolute value of the MSA beta. As shown in Figure 1-2, higher betas concentrate in coastal areas, while most of the inland MSAs have the beta below 1. Obviously, coastal MSAs are more sensitive to aggregate real estate shocks. Among the 25 MSAs having a beta higher than 1, only 3 are inland.

[5] Alternatively, MSA beta can also be calculated using data from 1998 to 2015, which covers the same period as the REITs' return. The results based on MSA beta over the period from 1998 to 2015 are even stronger.

[6] The NPI returns are, of course, subject to appraisal smoothing effects, which are acknowledged and the issue is addressed in a later robustness test. .

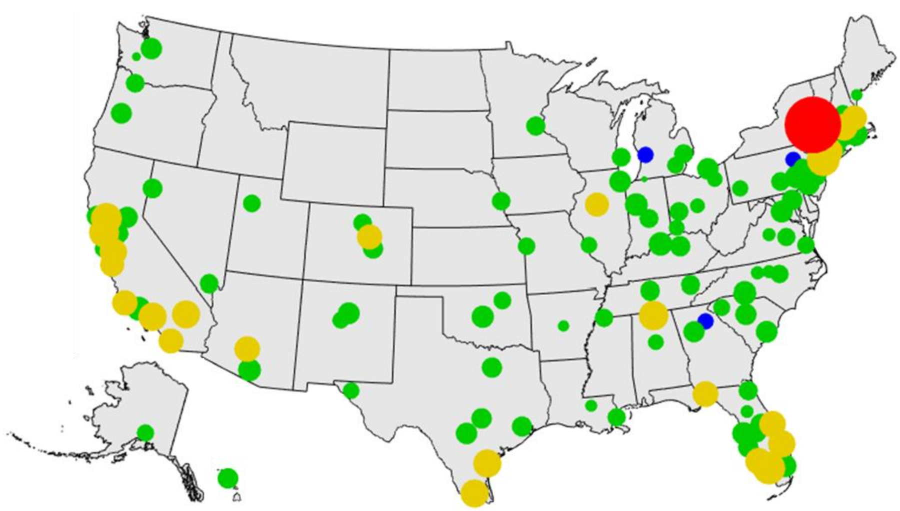
Figure 1: Distribution of MSA Betas

Figure 1-1: Histogram



Note: The figure plots the histogram distribution of MSA betas.

Figure 1-2: Geographic Distribution



Note: The figure plots the geographic distribution of MSA betas. The red dot denotes a beta higher than 2, the yellow dot denotes a beta between 1 and 2, the green dot denotes a beta between 0 and 1 and the blue dot denotes a beta less than 0. The size of the dots is proportional to the absolute value of the MSA beta.

Table 1: Descriptive statistics for return data and firm characteristics

	Mean	Std. Dev.	Max	Min
Return data				
REIT Return	0.074	0.513	12.531	-5.205
NCREIF Return	0.076	0.067	2.145	-1.746
Fama–French Factor				
Market	0.078	0.196	28.375	-22.375
SMB	0.025	0.097	11.200	-10.800
HML	0.029	0.104	12.075	-10.550
MOM	0.047	0.083	11.300	-7.575
NAREIT index Return	0.105	0.279	42.121	-54.224
Firm characteristics				
Market Capitalization (Billion USD)	2.639	3.796	26.068	0.000
Price to Book Ratio	2.044	1.185	7.439	0.017
RE Investment Growth (%)	0.150	0.337	3.105	-0.984
Debt to Equity	1.864	3.494	31.125	0.001
MSA unemployment rate	6.038	1.872	14.350	2.650
HHI MSA	0.199	0.236	1	0.013
NOI (100 Million USD)	23.653	19.439	338.454	-0.031
GA expenses (100 Million USD)	9.712	1.435	13.194	3.526
Density	101	73	583	5

Table 2: Descriptive statistics for estimated beta

	Mean	Std. Dev.	Max	Min
Real estate market beta				
Market beta	0.818	0.379	2.764	-0.587
Market beta_ rolling window	0.822	0.524	5.052	-1.096
Market beta_Leveraged Return	0.860	0.564	2.025	-3.201
Market beta_Desmoothed Leveraged Return	0.578	0.435	1.573	-1.773
REIT local beta				
Local beta	0.879	0.087	1.206	0.663
Local beta_rolling window	0.884	0.148	1.713	0.137
Local beta_instrumented weights	0.879	0.087	1.206	0.663
Local Beta_Leveraged Return	0.980	0.139	1.554	0.654
Local Beta_ Desmoothed Leveraged Return	0.703	0.159	1.235	0.178

Table 3 lists the MSAs with the lowest and highest betas, to shed more light on local betas. MSAs with the highest betas tend to experience higher property returns and larger standard deviation. This is consistent with the theory that property investors require a higher expected return to compensate for taking more risks. There is also a moderate positive relationship between the beta and the economic size of an MSA (as measured by gross domestic product, GDP) but no significant relationship between the local beta and the unemployment rate. Using MSA level unemployment rate and GDP for 2015, the correlation coefficient between MSA beta and GDP is 0.15 while the correlation coefficient with the unemployment rate is insignificant.

Based on β_m and $w_{m.i,t}$, we calculate the local beta for each REIT based on their property portfolio. The estimated local beta for each REIT is summarised in Table 3. The average $\beta_{i,t}^{local}$ is 0.88 and the standard deviation is quite small, only 0.09. The maximum local beta is 1.21, and the minimum is 0.66. Obviously, the firm level local beta has a much smaller standard deviation than the MSA betas. The reason is that most REITs have well-diversified property portfolios. On average, properties in each REIT are distributed in 33 MSAs, with a minimum of one MSA and a maximum of 370. Therefore, the standard deviation of the firm local beta is much smaller than the real estate market beta. This is consistent with diversification theory. In a geographically diversified portfolio, local cyclical movements can counteract each other and, therefore, the total location risk taken by the firm can be reduced.

Table 3: Highest and Lowest Beta MSAs

The table shows summary statistics for the MSAs with the highest (Panel A) and lowest (Panel B) betas and the return statistics in these MSAs. Mean stands for the average annual returns of NCREIF total returns, and Std stands for the standard deviation of NCREIF total returns. GDP stands for Gross Domestic Product for all industries for each MSA in 2015 (millions of current USD). Ump. Rate stands for the unemployment rate for each MSA in 2015.

CBSA	MSA Title	β_m	Mean	Std	GDP 2015	Ump. Rate 2015
	Highest β_m					
10580	Albany–Schenectady–Troy, NY	2.764	0.142	0.103	51433	4.5
35620	New York–Newark–Edison, NY–NJ–PA	1.493	0.100	0.182	1618366	5.3
34940	Naples–Marco Island, FL	1.470	0.133	0.346	16791	5.3
34900	Napa, CA	1.382	0.084	0.185	10485	4.6
41884	Santa Cruz–Watsonville, CA	1.330	0.094	0.130	12846	7.5
26620	Huntsville, AL	1.310	0.087	0.095	24153	5.5
31080	Los Angeles–Long Beach–Santa Ana, CA	1.242	0.103	0.124	967100	6.1
18580	Corpus Christi, TX	1.232	0.107	0.121	22813	5.2
32580	McAllen–Edinburg–Pharr, TX	1.230	0.089	0.108	19102	7.9
31080	Louisville, KY–IN	1.228	0.096	0.115	967100	4.7
	Lowest β_m					
36100	Ocala, FL	0.411	0.023	0.139	7875	6.5
12940	Baton Rouge, LA	0.362	0.071	0.095	51980	5.5
38860	Portland–South Portland, ME	0.333	-0.003	0.161	29647	3.5
30780	Little Rock–North Little Rock, AR	0.321	0.116	0.119	37284	4.5
36500	Olympia, WA	0.190	0.097	0.103	10909	6
43780	South Bend–Mishawaka, IN–MI	0.030	-0.028	0.176	13583	5
39540	Racine, WI	-0.011	0.090	0.104	7917	5.6
42540	Scranton–Wilkes–Barre, PA	-0.557	0.124	0.109	22769	6.2
27600	Kansas City, MO–KS	-0.586	0.099	0.069	125765	4.8
24340	Grand Rapids–Wyoming, MI	-0.587	0.088	0.085	56275	3.9

3.2 Firm characteristics

Data concerning individual company characteristics are collected from SNL Financial. The returns and the market capitalisation data are from Thomson Reuters DataStream. We collect data for all available U.S. listed real estate companies[7] with assets' locational information between 1998 and 2015, a total of 202 real estate firms. Overall, 76% of properties in each firm are located in the 144 MSAs with NCREIF NPI property returns. 145 firms have over 70% of properties located in the

[7] All firms are REITs in 2015. But SNL keeps firm information before the firm was converted to REIT. If we exclude the observations before the REIT status was established, the results remain completely robust.

144 MSAs. Therefore, our results are based on these 145 firms. Due to missing values in other explanatory variables, the final sample consists of 99 REITs.

Table 2 summarizes the firm characteristics of the real estate companies, averaged across time, from 1998 to 2015, and across the 99 companies. The average annual return across all companies is 7.4%, with a standard deviation of 51%. We also see a large variation across the size of the companies in terms of market capitalisation, with the highest being \$26 billion and the lowest, \$0.35 million. On average, a company has a market capitalisation of \$2,627 million. The average market to book ratio (M/B) ratio is 2.04,. The average debt to equity (D/E) ratio is 1.86. The average real estate investment growth rate is 0.15%, with a maximum of 3.11% and a minimum of -0.98%. We also account for market power or market concertation using the Herfindahl–Hirschman Index (HHI) at the MSA level. The HHI measures the geographic concentration of properties of one firm across the MSAs:

$$HHI_{it} = \sum_{l=1}^{L} \left(\frac{P_{t,i,l}}{N_{t,i}}\right)^2, \tag{3}$$

where $P_{t,i,l}$ is the number of properties of firm *i* with *n*=1, 2,…, *N* that locate in MSA *l* with *l*=1, 2,…, *L* in year *t.* The HHI ranges from close to 0 to 1. If HHI has a value of one, it means that all properties of the firm are located in the same MSA. The lower the HHI value, the less concentrated are the firm's properties across the MSAs.

3.3 Stock market beta

Local beta reflects the risk exposure to the underlying real estate markets. As REITs are listed on the stock market, equity market risk exposure must also be considered. Equity market risk exposure is measured using a standard four factor model, with the sensitivity of a REIT's return to stock market return calculated as the conditional factor loading ($\beta_{i,t}^{stock}$) for firm *i* and year *t*:

$$r_{i,t,d}^{REIT} - r_{f,t,d} = \alpha_{i,t} + \beta_{i,t}^{stock} MKT_{t,d}^{stock} + \beta_{i,t}^{SMB} SMB_{t,d} + \beta_{i,t}^{HML} HML_{t,d} + \beta_{i,t}^{MOM} MOM_{t,d} + \varepsilon_{i,t,d}, \tag{4}$$

where $r_{i,t,d}^{REIT}$ is the daily return in day *d* in year *t* for firm i and $r_{f,t}$ is the corresponding risk-free rate as measured by the yield on the 1-month Treasury bill.

The factors comprise a US market return index (MKT), the difference between the returns on diversified portfolios of small stocks and big stocks (SMB) and the difference between the returns on diversified portfolios of high M/B (value) stocks, low M/B (growth) stocks (HML), and the difference between the monthly returns on diversified portfolios of winners and losers over the past year (MOM). For consistency with prior research, the factors are obtained from Ken French's website. As shown in Table 2, REITs have been more volatile than general stock markets over the period from 1998 to 2015, and REIT investors also received a slightly higher return as compared to general stock investors.

4 Empirical Results

4.1 Cross-sectional Fama–MacBeth Regression Results

A Fama–MacBeth cross-sectional regression is conducted to identify whether the location risk has been priced in REIT equity returns. The Fama–MacBeth regression is run in two stages. In the first stage, for each year of our sample period, we estimate the following cross-sectional regression:

$$r_{i,t}^{REIT} - r_{f,t} = c_0 + \gamma^{\text{RE local}} \beta_{i,t-1}^{\text{RE}\,local} + \gamma^{\text{Stock Mrkt}} \beta_{i,t-1}^{stock} + \sum_{k=1}^{K} c_{i,k} X_{k,i,t} + e_{i,t}, \quad (5)$$

where $r_{i,t}^{REIR} - r_{f,t}$ is the firm's annual excess return with respect to the yield on the 1-month Treasury bill. $X_{m,i,t}$ is one of the following K firm characteristics: the change in SIZE, defined as the log-differenced firm's aggregate market capitalization; M/B, defined as the market value of assets divided by the book value of assets; LEV, defined as total debt divided by the book value of equity; and RE Invest, the real estate investment growth and MSA level unemployment rate. We also include property type dummy variables. In the second stage, we use the time series of the regression coefficients and test if the average coefficient is significantly different from zero. To take into account serial correlation in the coefficient estimates, we compute Newey–West standard errors with four lags in the second stage. By comparing $\gamma^{\text{RE local}}$ and $\gamma^{\text{Stock Mrkt}}$, we identify changes in the REIT price triggered by the systematic risks from direct real estate market and equity markets.

Table 4 presents the main results starting with Model 3(in Models 1 and 2, only local beta or stock beta is included). In Model 4, instead of contemporaneous control variables ($X_{k,i,t}$), lagged control variables are used ($X_{k,i,t-1}$). In Model 5 and 6, more control variables are included. The results confirm that, with the increase in location risks, REIT returns increase significantly. The coefficient for lagged local beta remains significant in all specifications. Investors require a higher return to compensate for a higher exposure to riskier local property markets. This finding differs from that in Tuzel and Zhang (2017). They show that stock returns are significantly *negatively* related to local risk, in particular for firms with low real estate assets. This finding by Tuzel and Zhang (2017) supports their wage hedging mechanism – that is, more cyclical wages absorb part of the aggregate shocks and therefore reduce the risk relative to industry peers located in the low beta area. The finding of this paper confirms the importance of the real estate channel for real estate firms. The exposure to a more cyclical real estate market (high beta markets) increases the perceived risk of firms' equity. Therefore, investors require a higher reward to compensate for the additional risk they take.

Regarding the dual nature of REITs, the sensitivity to real estate and stock market risk can be compared based on the size of the corresponding coefficient. Economically, a one standard deviation change in the local beta will result in a 1.4% increase in REIT returns (Model 3)[8]. A one standard deviation change in stock beta is related to a 2.1% increase in REIT returns[9], which is about 1.5 times higher than the sensitive reaction to real estate betas. This finding is consistent with the previous REIT literature. In the short term, the stock market plays a more dominant role in REIT performance. However, in the following section, we shall show that this conclusion may not be applicable to all REITs. The sensitivity to real estate market risk depends on the diversification strategy of REITs.

The regression results for the control variables are consistent with previous literature (Table 4, Model 3). Firms with increasing size, a higher M/B ratio and lower financial constraints have higher returns. Real estate investment growth has a negative coefficient; this can be explained by the fact that high investment growth may result in higher management costs and therefore reduce

[8] The economic impact is calculated as the coefficient multiplied by the standard deviation of the local beta, which is 0.087.

[9] The economic impact is calculated as the coefficient multiplied by the standard deviation of the stock beta, which is 0.443.

the equity returns of REITs. The unemployment rate of MSAs where REITs' property is located is significantly negatively related to the REIT returns, confirming that the economic environment or the business cycle in local markets also affect REITs performance.

In Model 5, risk exposure to other Fama–French-Carhart factors are also included. As shown in Table 4, the coefficient for local beta remains significant.As high exposure to risky real estate markets may have an impact on operating cash flows and management costs, the relationship between local beta and REIT excess returns may actually be caused by the underlying property cash flows. Therefore, in Model 6, we include Net Operating Income (NOI) and G&A expenses as additional control variables. Furthermore, as shown by Tuzel and Zhang (2017), firm equity return may be affected by the local risk in the headquarter of the firm. The MSA beta where the REIT's headquarter locates is also included as an additional control variable to investigate whether the riskiness of the local property market is transmitted into REIT performance via the location of the headquarter or the location of the assets. We also use the residential market performance to proxy for the local demand and supply for real estate and even the credit supply in the local markets, as the recent housing boom is believed to closely relate to the excess credit supply to the real estate markets in general. As the local beta of individual REITs is strongly related to the geographic diversification strategy of REITs, we include the Herfindahl index for the MSA level focus of assets[10]. Additionally, location risks may also be strongly related to property density. In most downtown areas, the market would be more liquid. Therefore, concerns could arise that the location risks may only capture the impact of investing in downtown or suburban areas – the density of the location, rather than the liquidity risk. We, therefore, also control the density of properties in Model 6. We add another control variable – the average number of properties held by any other REIT located within a 5 km radius of each individual property.[11] Overall, the results remain robust. The coefficient for local beta remains significant throughout.

[10] We acknowledge that there could be potential multicollinearity between local beta and a REIT's HHI index, as in our later analysis, local beta is found to significantly decrease with HHI index. The multicollinearity problem may result in an increase in the standard error of the coefficients. Therefore, we do not include HHI index in the baseline model. Here, we would like to show that local beta can add more information to our understanding of REITs returns: more than can be explained by geographic diversification strategies which do not disentangle the riskiness of the underlying markets.

[11] We count the number of properties surrounding each property held by a REIT, and then calculate the average number for that REIT, given the total number of properties held by that REIT. It should be noted that, since we only have the information about the properties held by REITs, the density is measured by the properties held by REITs, not the full property universe.

Table 4: Local Beta and Firm Returns

Note: This table reports the results of Fama–MacBeth cross-sectional regression. The dependent variable is the annual excess return netting of the T-bill rate. . $r^{REIT}_{firm,t-1}$ is the lagged return. $\beta^{RE\ local}_{firm,t-1}$ stands for the lagged local beta for firm i. $\beta^{Stock\ Mrkt}_{firm,t-1}$ is for the lagged stock market beta. $\beta^{SMB}_{i,t-1}$, $\beta^{HML}_{i,t-1}$, and $\beta^{MOM}_{i,t-1}$ are the beta for Fama–French factors. Control variables include headquarter MSA beta, net operating income (NOI), G&A expenses (GA), change in market value, debt to equity ratio, market to book ratio, real estate investment growth and property type dummy. Standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Model 1:	Model 2:	Model 3:	Model 4:	Model 5:	Model 6:
$\beta^{RE\ local}_{firm,t-1}$	0.1538**		0.1703**	0.1509***	0.1322**	0.1892**
	(0.0725)		(0.0687)	(0.0387)	(0.0643)	(0.1042)
$\beta^{Stock\ Mrkt}_{firm,t-1}$		0.0512**	0.0478**	0.0938***	0.0564*	0.0534**
		(0.0232)	(0.0271)	(0.0268)	(0.0367)	(0.0219)
$r^{REIT}_{i,t-1}$	-0.1055**	-0.0532*	-0.1218**	-0.0914	-0.0811*	-0.1391**
	(0.0595)	(0.0362)	(0.0643)	(0.1566)	(0.0586)	(0.0565)
Change in Size	4.9540***	4.8918***	5.1065***	0.3939	4.6783***	4.9686***
	(0.8206)	(0.9040)	(0.8231)	(0.7776)	(0.9481)	(0.7164)
Market to	0.0366***	0.0355***	0.0345***	0.0044	0.0332***	0.0278*
Book	(0.0114)	(0.0097)	(0.0115)	(0.0204)	(0.0109)	(0.0169)
RE Investment Growth	-0.1115**	-0.1437***	-0.1027**	-0.0047	-0.0970**	-0.1365**
	(0.0551)	(0.0402)	(0.0498)	(0.0487)	(0.0398)	(0.0537)
Debt to Equity	-0.0071**	-0.0019**	-0.0059**	-0.0022	-0.0061**	-0.0055**
	(0.0039)	(0.0010)	(0.0031)	(0.0026)	(0.0031)	(0.0028)
MSA_Ump	-0.0164	-0.0062	-0.0175*	0.0253	-0.0238**	-0.0299***
	(0.0127)	(0.0079)	(0.0104)	(0.0183)	(0.0118)	(0.0098)
$\beta^{SMB}_{i,t-1}$					0.0133	
					(0.0456)	
$\beta^{HML}_{i,t-1}$					-0.0193	
					(0.0391)	
$\beta^{MOM}_{i,t-1}$					-0.0266	
					(0.0515)	
β^{head}_{i}						-0.0220
						(0.0532)
Regional Focus (HHI)						0.0347
						(0.0760)
MSA_dHP						1.3482
						(1.2521)
NOI						-0.0022
						(0.0018)
GA expenses						0.0113
						(0.0172)
Property Density						-0.0211
						(0.0290)
Property Type Dummy	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs	1158	1158	1158	1078	1158	1145
Adj. R2	0.8017	0.8232	0.8072	0.8196	0.8886	0.8037

4.2 Geographic Diversification and Local Betas

The above analyses confirm that location risks get priced into the firm's equity price via the real estate channel. For a firm with high exposure to high beta areas, the value of its underlying assets would respond more strongly to aggregate shocks than a low exposure to the high beta area. Therefore, investors would perceive a higher equity risk for firms in high beta areas than for firms in low beta areas and therefore require a higher reward for taking that risk. If this real estate channel really matters, one would expect a lower sensitivity of REIT returns to $\beta_{i,t}^{local}$ for geographically well-diversified REITs than for concentrated REITs. The real estate channel should be more pronounced for more concentrated REITs.

In order to test this argument, we split the sample into well and less diversified REITs according to the geographic location of property portfolios. We first assess whether diversification can significantly reduce $\beta_{i,t}^{local}$. We then estimate the sensitivity of REIT returns to $\beta_{i,t}^{local}$ for diversified and specialised REITs separately. By regressing $\beta_{i,t}^{local}$ on HHI_{it}, we test whether geographic diversification can significantly reduce location risks. The results are reported in Table 5. As expected, concentration significantly increases $\beta_{i,t}^{local}$. When REITs employ a more diversified investment strategy, the firm is exposed to a lower degree of location risks.

We then split REITs into two groups: 50% of the firm with more concentrated assets and 50% of firms with more diversified assets according to their HHI values. The results for these two groups of firms are reported in Model 8 and 9 in Table 5. For the 50% of REITs with more diversified assets, the coefficient for $\beta_{i,t}^{local}$ is insignificant. Real estate risks are not priced in the equity return, implying that investors may decide that the location risks can be ignored due to diversification. But for the 50% of REITs with less diversified assets, the coefficient for $\beta_{i,t}^{local}$ rises to 0.2751. We further split the sample into 33% of the most concentrated firms and the rest, as shown in Model 10 and 11. With the increase in the concentration threshold, the sensitivity to location risks increases further to 0.6479. This implies that a one standard deviation increase in the location risks will be related to up to a 5.6% increase in the equity return. For more concentrated REITs, the sensitivity to stock market risk also increases to 0.0943, which implies an impact of 4.2%, which is lower than real estate risk. Overall, geographic diversification helps REITs to reduce their sensitivity to real estate and stock market risks.

Using the number of MSAs where properties are located generates similar results. With the increase in the number of MSAs, location risk decreases significantly. When a REIT holds properties over 13 or more MSAs, location risks are not priced in REIT equity returns. Since the location risk is, by definition, systematic, it cannot be diversified away in a REIT portfolio and hence is priced, just as with equity market risk sensitivity.

4.3 Robustness Checks

4.3.1 Self-selection

We further consider the situation that $w_{m.i,t}$ may be affected by the potential self-selection in some REITs having a bias for less risky and more liquid real estate markets. We use the distance to headquarters as the instrument for $w_{m.i,t}$. Based on the home bias theory, the distance of assets to the headquarters can be a good predictor for the firm's asset allocation. Market participants often choose local investment to reduce information asymmetry in opaque information environments (Garmaise and Moskowitz, 2004). Ling et al. (2018b) also show that managers overweight asset allocations to their local market. Therefore, the distance of properties to the headquarters can be a relevant instrument. For each firm, we regress the proportion of properties in MSA *m* on the distance to the headquarters:

$$w_{m.i,t} = a_i + b_i \ln D_{m,i,t} + e_t, \qquad (6)$$

where $D_{m,i,t}$ is the average distance of properties located in the MSA *m* to the headquarters of REIT *i*. For instance, if two properties are located in MSA *m*, $D_{m,i,t}$ is the average distance of these two properties to the headquarters of the firm. For the estimation of Equation (6), it is required that the firm has investments on at least three different MSAs. For firms with properties located in only one or two MSAs, we use the observed weights. The estimated b_i is illustrated in Figure 2a. Most of the coefficients are negative. The average coefficient is –0.056 and the average T statistic is –1.96. So the instrumented weight is calculated as $\widehat{w}_{m.i,t} = \hat{a}_i + \hat{b}_i \ln D_{m,i,t}$ and the local beta is calculated as $\beta_{i,t}^{local} = \sum_{m=1}^{M} \widehat{w}_{m.i,t} \beta_m$. The estimated results based on instrumented weights are reported in Table 6, Model 17. The coefficient rises to 0.22.

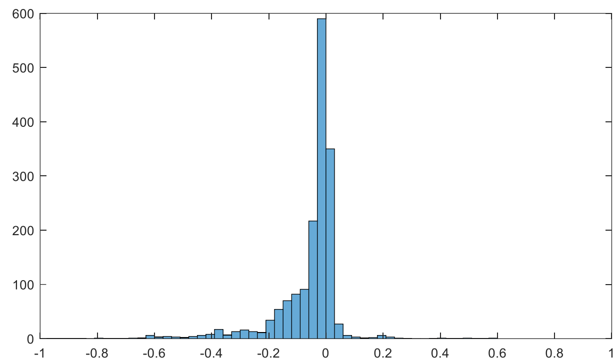
Table 5: Local Beta and Diversification

Note: This table reports the results of Fama–MacBeth cross-sectional regression. The dependent variable for Model 14 and 19 is the local beta. The dependent variable from Model 15 to 18 and from Model 20 to 23 is the annual excess return netting of the T-bill rate. $r_{firm,t-1}^{REIT}$ is the lagged return. $\beta_{firm,t-1}^{RE\ local}$ stands for the lagged local beta for firm i. $\beta_{firm,t-1}^{Stock\ Mrkt}$ is for the lagged stock market beta. Control variables include the change in market value, debt to equity ratio, market to book ratio, real estate investment growth and property type dummy. Standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: HHI					
		Return			
	Model 7: β_{firm}^{local}	Model 8: concentrated HHI>0.14	Model 9: diversified HHI<=0.14	Model 10: concentrated HHI>0.25	Model 11: diversified HHI<=0.25
HHI	0.0430**				
	(0.0170)				
$\beta_{firm,t-1}^{RE\ local}$		0.2751***	-0.0752	0.6479***	0.0399
		(0.0687)	(0.0801)	(0.1801)	(0.1348)
$\beta_{firm,t-1}^{Stock\ Mrkt}$		0.0880**	-0.0402	0.0943**	-0.0162
		(0.0387)	(0.0421)	(0.0437)	(0.0380)
Control Variables	Yes	Yes	Yes	Yes	Yes
Property Type Dummy	Yes	Yes	Yes	Yes	Yes
No. of obs	1164	514	644	369	789
Adj. R2	0.0540	0.8005	0.8562	0.9045	0.7759
Panel B: Number of MSAs					
		Return			
	Model 12: β_{firm}^{local}	Model 13: concentrated MSA<=20	Model 14: diversified MSA>20	Model 15: concentrated MSA<=13	Model 16: diversified MSA>13
Log(MSA)	-0.0004***				
	(0.0000)				
$\beta_{firm,t-1}^{RE\ local}$		0.1927**	-0.0451	0.2420**	-0.0320
		(0.1064)	(0.0886)	(0.1284)	(0.0424)
$\beta_{firm,t-1}^{Stock\ Mrkt}$		0.0728*	0.0311	0.0642	0.0523
		(0.0483)	(0.0431)	(0.0555)	(0.0409)
Control Variables	Yes	Yes	Yes	Yes	Yes
Property Type Dummy	Yes	Yes	Yes	Yes	Yes
No. of obs	1164	459	699	374	784
Adj. R2	0.0740	0.8281	0.8305	0.7863	0.8295

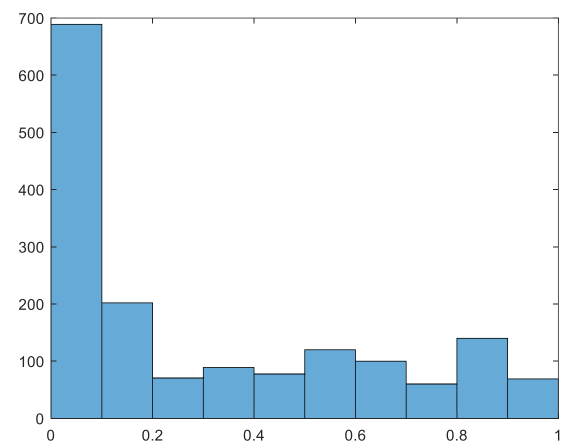
Figure 2: Distance as the Instrument

Figure 2a Coefficient of Distance



Note: The figure plots the distribution of the coefficient for the distance in the auxiliary regression for the instrumented proportion of properties in each MSAs. The proportion of properties for a certain MSA is regressed on the average distance of all properties held this firm located in a certain MSA to the headquarter of the firm. The regression is run separately for each firm.

Figure 2b F test for the Relevance of Distance



Note: This graph shows F statistics for the relevance test of the instrument. The x-axis is the p-value of the test, and y-axis is the frequency of each p-value. Among the 1618 year-firm observations, 689 (42%) have the p-value lower than 10%.

However, previous literature shows that REIT performance can be affected by the geographic diversification of underlying assets or the share of the assets locating in the home MSAs, which may challenge the exogeneity of the instrument. Therefore, the share of home assets (Model 18) and the Herfindal asset concentration indicator (Model 19) are also controlled. We argue that this instrument is conditionally exogenous given control of the diversification strategy. A further concern could be that firms' performance can also be affected by being local or dispersed. For instance, Garcia and Norli (2012) find that local firms have lower investor recognition, which implies a higher required return in their equity. It should be noted that we are not using the absolute distance, but the relative distance of each property to the headquarters, as the instrument, separately for each firm. Therefore, this instrument is not affected by whether the firm is a local firm or dispersed firm. It is independent from the average distance of the assets to the headquarter. If firm A has all assets in one distant MSA, and if firm B has all assets in its headquarter MSAs, the weights for both firms are 1, although firm A is a dispersed firm and firm B is a local firm.

Although we are able to argue the exogeneity of distance to the MSA real estate market performance, the relevance of the instrument needs may not be satisfied. We follow the classical F test for the validity of the instrument. However, in our paper, we run the first stage regression (Equation 6) for each firm in each year. So in total, we have 1618 regressions in the first stage. The p-value of the F statistic in each first stage regression is plotted out in Figure 2b. The x-axis is the p-value of the test, and the y-axis is the frequency of each p-value. Around 43% of the regressions have the p-value lower than 10%. In order to make sure the relevance of the instrument, we exclude those firm-year observations with an insignificant F-test and construct $\widehat{w}_{m,i,t}^{sig}$ using only observations with significant F-tests. The results are reported in Table 6, Model 20. Due to the reduction in the number of $\widehat{w}_{m,i,t}^{sig}$ decreases, the total number of observations in the second stage (Model 20) is reduced by nearly half. However, even with this conservative adjustment, the coefficient remains significant.

Since the number of observations decreases by nearly half, we further test whether the remaining sample is still representative using a Heckman correction. We first investigate the probability of surviving (Equation 7), and then include the Inverse Mill's ratio of the estimated probability as an additional regressor to correct for potential selection bias (Equation 8):

$$\mathrm{Prob}_{\mathrm{i,t}} = c + dX_{i,t} + \gamma_i + \delta_t + u_{i,t}, \tag{7}$$

$$y_{i,t} = \alpha \mathrm{T}_{i,t-1} + \beta X_{i,t} + \theta \widehat{\mathrm{Mill}}_{\mathrm{i,t}} + \gamma_i + \delta_t + e_{i,t}, \tag{8}$$

The dependent variable for Equation (8) is a dummy variable with the value of one when the F test is significant at the 10% level, and zero when the F test is insignificant. In other words, a significant F test means that the distance to the headquarters is a valid instrument for this firm at this period. This REIT is more likely to allocate assets in its local markets. The results of Equation 8 is shown in Table 6, Model 21. The coefficient for the local beta again remains significant and of comparable magnitude to the other specifications.

4.3.2 Time-Varying MSA Beta

The MSA beta based on Equation 2 is constant over time, which allows us to capture the average cyclicality of each property market. We also investigate the time-varying local beta using a 30 quarter rolling window, to allow for possible structural changes in property market volatility.

$$r^{NPI}_{m,(\mathrm{q}-30,\mathrm{q})} - r_{f,(\mathrm{q}-30,\mathrm{q})} = \alpha_{m,q} + \beta_{m,q}(MKT^{NPI}_{(\mathrm{q}-30,\mathrm{q})} - r_{f,(\mathrm{q}-30,\mathrm{q})}) + \varepsilon_{m,q}. \quad (9)$$

where $r^{NPI}_{m,(\mathrm{q}-30,\mathrm{q})}$ is the NPI return over the past 30 quarters at period q in MSA m. Based on the leveraged NPI returns, the mean of $\beta_{m,q}$ slightly increases to 0.822 and the standard deviation grows to 0.564. The larger standard deviation in the MSA beta could be due to the smaller number of observations in the regression. As shown in Figure 3-a, the beta distribution shows obviously heavier tails. We then calculate the local beta based on the rolling MSA betas. However, given the fact that some MSAs have NPI returns for less than 30 quarters, many missing values appear. When there is missing value in the rolling window MSA beta, we use the average MSA beta as a substitute. The summary statistics are reported in Table 2; the local beta with rolling MSA beta has a very similar mean but a much larger standard deviation. The Fama Macbeth regression results are reported in Table 7. The results are robust with the local beta coefficient remaining significant with a value of 0.18 (Model 22).

Table 6: Robustness Checks: Self Selection

Note: This table reports the results of Fama–MacBeth cross-sectional regression. The dependent variable is the annual excess return netting of the T-bill rate. $r_{firm,t-1}^{REIT}$ is the lagged return. $\beta_{firm,t-1}^{RE\ local}$ stands for the lagged local beta for firm i. $\beta_{firm,t-1}^{Stock\ Mrkt}$ is for the lagged stock market beta. Control variables include the change in market value, debt to equity ratio, market to book ratio, real estate investment growth and property type dummy. Standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Model 17: Instrumented weights	Model 18: Instrumented weights	Model 19: Instrumented weights	Model 20: Instrumented weights_SigFtest	Model 21: Instrumented weights _Heckman
$\beta_{firm,t-1}^{RE\ local}$	0.2273**	0.2425**	0.2188***	0.2578***	0.1719**
	(0.1037)	(0.1152)	(0.0790)	(0.0973)	(0.0862)
$\beta_{firm,t-1}^{Stock\ Mrkt}$	0.0638**	0.0630***	0.0641***	0.0119	0.0134
	(0.0253)	(0.0211)	(0.0227)	(0.0356)	(0.0429)
$r_{firm,t-1}$	-0.0848**	-0.0870***	-0.0866***	-0.1815**	-0.1325**
	(0.0434)	(0.0118)	(0.0117)	(0.0728)	(0.0688)
Change in Size	4.9314***	4.9359***	5.0071***	6.1245***	7.3712***
	(0.8699)	(0.8503)	(0.8214)	(1.3109)	(1.1242)
Market to Book	0.0383***	0.0348***	0.0351***	0.0266***	0.0286**
	(0.0106)	(0.0096)	(0.0085)	(0.0085)	(0.0122)
RE Invest. Growth	-0.0840**	-0.1054***	-0.0989***	0.0032	0.0172
	(0.0346)	(0.0289)	(0.0380)	(0.0772)	(0.0692)
Debt to Equity	-0.0043**	-0.0038***	-0.0032**	-0.0012	-0.0043
	(0.0023)	(0.0015)	(0.0015)	(0.0024)	(0.0033)
MSA_ump	-0.0204	-0.0325**	-0.0263*	-0.0167	-0.0076
	(0.0155)	(0.0143)	(0.0149)	(0.0197)	(0.0113)
Home Assets		0.0253			
		(0.0522)			
HHI			0.0335		
			(0.0497)		
Prob.					0.1482
					(0.1230)
Property Type Dummy	Yes	Yes	Yes	Yes	Yes
No. of obs	1274	1274	1273	639	610
Adj. R2	0.8049	0.8063	0.8050	0.7809	0.8337

4.3.4 Sector MSA Beta

Our MSA beta is calculated using properties in all sectors. However, different property sectors may be subject to different levels of risk. The local beta should match REITs against the relevant NPI sectors. The NPI NCREIF Property Index includes Apartment, Hotel, Industrial, Office, Retail and other properties. However, the sector MSA data is quite limited with many missing observations. Due to limitation of the data, we split the sectors into two broad categories: commercial and residential. We then calculate the beta separately for each sector:

$$r_{m,q}^{NPI,Residential} - r_{f,q} = \alpha_m + \beta_m^{residential}(MKT_q^{NPI,Residential} - r_{f,q}) + \varepsilon_{m,q}, \quad (10)$$

$$r_{m,q}^{NPI,Commercial} - r_{f,q} = \alpha_m + \beta_m^{commercial}(MKT_q^{NPI,Commercial} - r_{f,q}) + \varepsilon_{m,q}, \quad (11)$$

$$\beta_{i,t}^{local} = \sum_{m=1}^{M} w_{m.i,t}^{residential} \beta_m^{residential} + \sum_{m=1}^{M} w_{m.i,t}^{commercial} \beta_m^{commercial}. \quad (12)$$

We report the results based on two-sector MSA beta in Table 7 Model 23, which again are robust, albeit with a fall in the magnitude of the local beta coefficient.

4.3.5 Leverage and Valuation Smoothing

The validity of the NCREIF NPI index is sometimes questioned. One concern is about leverage. REIT performance indices embed the impact of leverage, but NCREIF NPI returns are reported on an unlevered basis. Hoesli and Oikarinen (2012) show that the magnitude of leverage can affect the mean and the volatility of REITs. In an additional robustness check, we use the leveraged NPI NCREIF returns. However, not all properties in the NCREIF database report leverage, so the leveraged return covers much fewer properties in each MSA and only 109 MSAs have NCREIF leveraged return data over 10 quarters. So β_m^{LEV} and $\beta_{i,t}^{LEV,local}$ is calculated based on a smaller sample.

Based on the leveraged NPI returns, the mean of β_m^{LEV} rises to 0.860 and the standard deviation grows to 0.564. Both are higher than using unleveraged total returns (Table 2). Baton Rouge, LA, MSA even has a very negative β_m of –3.5. The reason is that when the total return of unleveraged projects is lower than the interest rate, leverage actually has a negative impact on the leveraged return. The overall distribution of β_m^{LEV} is shown in Figure 3. With a higher and more volatile β_m^{LEV}, the real estate risk exposure of REITs also increases. The average $\beta_{i,t}^{LEV,local}$ rises to 0.98 and the standard deviation increases to 0.139. As leverage influences financial risk, the real estate risk taken by REITs is amplified by the use of leverage. The Fama–MacBeth regression results based on $\beta_{i,t}^{LEV,local}$ are also reported in Table 7. Compared to the baseline model (Model 1), the size of the coefficient slightly decreases to 0.16, but remains statistically significant. However, due to the increase in the standard deviation of $\beta_{i,t}^{LEV,local}$, the economic impact slightly increases based on the leveraged returns. A one standard deviation increase in the risk exposure to local real estate markets is associated with a 1.4% increase in the equity returns of REITs.

Appraisal smoothing is another concern. NCREIF returns are appraisal-based, which may lead to smoothing if appraisers anchor on prior values. To extract the true returns, a desmoothing procedure must be used (Geltner et al., 2003, Lizieri et al., 2012). The simplest is a first-order autoregressive reverse filter. Equation (2) provides the smoothed total returns for direct real estate investment. Now we look at the leveraged NPI return as a combination of the current true real estate return and a lagged component for the prior index value:

$$r_{m,t}^{Lev} = (1-\gamma_m) r_{m,t}^{True} + \gamma_{\mathrm{m}} r_{m,t-1}^{Lev}, \tag{14}$$

where $r_{m,t}^{True}$ denotes the true underlying real estate returns. γ_m is the smoothing parameter for MSA *m* and can be calculated as the first-order autoregressive coefficient for the NPI returns. By re-arranging Equation (14), $r_{m,t}^{True}$ can be derived as:

$$r_{m,t}^{True} = \frac{r_{m,t}^{Lev} - \gamma r_{m,t-1}^{Lev}}{1-\gamma}. \tag{15}$$

Based on $r_{m,t}^{True}$, $\beta_m^{DeSm,Lev}$ s and the corresponding $\beta_{i,t}^{DeSm,Lev,local}$ for REITs are re-estimated based on Equation (16) and (17):

$$r_{m,t}^{True} - r_{f,t} = \alpha_m + \beta_m^{DeSm,Lev} (MKT_t^{True} - r_{f,t}) + \varepsilon_{m,t}. \tag{16}$$

$$\beta_{i,t}^{DeSm,Lev,local} = \sum_{m=1}^{M} w_{m.i,t} \beta_m^{DeSm,Lev}. \tag{17}$$

After de-smoothing the return series, β_m^{DeSm} decreases obviously, with a mean of 0.578 and standard deviation of 0.433. As a result, $\beta_{i,t}^{DeSm,local}$ is also lower than $\beta_{i,t}^{local}$. The Fama–MacBeth regression results are quite robust. The coefficient for real estate local beta remains very robust (Table 7 Model 24).

4.2.6 Further Robustness Tests

In our local beta calculation, we have some MSAs with a significant negative beta, whose inclusion be controversial givenstandard expectations. The negative beta might be caused by the short return periods and/or the small sample included in the NCREIF NPI database for these MSAs. In other words, the estimated beta for these MSAs might not be reliable. So, we exclude MSAs with a negative beta and re-run the regression. The results are presented in Table 7, Model 25. The coefficient for local beta remains robust.

Instead of using the national aggregated real estate returns, we also follow Tuzel and Zhang (2017) and use aggregated GDP change in the calculation of local beta. In this way, the local beta reflects the sensitivity of local real estate market performance on national economic shocks. The results are reported in Table 7, Model 26, which is robust.

A further concern could be the coincidence of returns and local beta, particularly during the period 2009 to 2014. Over this period, REIT market capitalisation increases at nearly 19% per annum, so there is a massive increase in listed real estate equity. Over the same time, price growth is more than 9% p.a., which is higher than the long run average. It may be that the local beta increases over that period (for example via more exposure to gateway cities) coinciding with higher returns and thus pushing up the explanatory power of the local beta.

We employ two robustness checks to address this issue. First, we exclude the period 2007-2015 when we calculate the MSA beta (Equation 2). The local beta is now estimated without any influence of the volatile period on property market performance. We then estimate the relationship between REIT return and local beta. Second, we still calculate MSA beta (Equation 2) using the full sample, but we only include the before-crisis period (1999-2006) when we calculate the impact of local beta on REIT returns (Equation 5). As shown in Table 7, Model 27 and 28, the influence of local beta on REIT returns becomes weaker in both tests, with significance falling to the 0,1 level, which may be due to the mismatch of the sample period of local beta and returns.

Table 7: Further Robustness Checks

Note: This table reports the results of Fama–MacBeth cross-sectional regression. The dependent variable is the annual excess return netting of the T-bill rate. $r^{REIT}_{firm,t-1}$ is the lagged return. $\beta^{RE\ local}_{firm,t-1}$ stands for the lagged local beta for firm i. $\beta^{Stock\ Mrkt}_{firm,t-1}$ is for the lagged stock market beta. Control variables include the change in market value, debt to equity ratio, market to book ratio, real estate investment growth and property type dummy. Standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Model 22: Time Varying MSA beta	Model 23: Sector MSA beta	Model 24: Leveraged and Desmoothed returns	Model 25: Excluding Negative Beta	Model 26: Using GDP shock	Model 27: Excluding 2007-2015 in beta calculation	Model 28: Excluding 2007-2015 in Return Calculation
$\beta^{RE\ local}_{firm,t-1}$	0.1800**	0.0788**	0.1327***	0.1777***	0.0724***	0.0626*	0.1321*
	(0.0840)	(0.0320)	(0.0422)	(0.0635)	(0.0201)	(0.0387)	(0.0845)
$\beta^{Stock\ Mrkt}_{firm,t-1}$	0.0401*	0.0484**	0.0159	0.0418*	0.0467**	0.0559**	-0.0062
	(0.0266)	(0.0267)	(0.0299)	(0.0281)	(0.0243)	(0.0289)	(0.0163)
$r_{firm,t-1}$	-0.1166**	-0.1193**	-0.1396**	-0.1279**	-0.1232**	-0.1338**	-0.1413**
	(0.0606)	(0.0643)	(0.0575)	(0.0629)	(0.0613)	(0.0692)	(0.0742)
Change in	5.2273***	5.0915***	5.1402***	5.1645***	5.0960***	5.1377***	3.6166***
Size	(0.8378)	(0.8321)	(0.7188)	(0.7987)	(0.7977)	(0.8113)	(0.3944)
Market to	0.0352***	0.0341***	0.0418***	0.0349***	0.0326***	0.0390***	0.0308**
Book	(0.0104)	(0.0113)	(0.0104)	(0.0115)	(0.0111)	(0.0101)	(0.0138)
RE Invest.	-0.1134**	-0.1081**	0.0005	-0.1029**	-0.1306***	-0.1108**	-0.0017
Growth	(0.0493)	(0.0481)	(0.1217)	(0.0487)	(0.0470)	(0.0485)	(0.0166)
Debt to	-0.0058**	-0.0062**	-0.0033	-0.0060**	-0.0060**	-0.0107**	-0.0054***
Equity	(0.0030)	(0.0030)	(0.0095)	(0.0031)	(0.0029)	(0.0052)	(0.0021)
MSA_ump	-0.0245*	-0.0137*	-0.0250**	-0.0178**	-0.0193**	-0.0048	-0.0224**
	(0.0145)	(0.0093)	(0.0131)	(0.0099)	(0.0106)	(0.0073)	(0.0086)
Property Type Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs	1154	1158	584	1144	1180	1023	478
Adj. R2	0.8566	0.8506	0.9033	0.8066	0.8106	0.8109	0.5976

Figure 3: Distribution of MSA betas

Figure 3a: Time Varying MSA betas

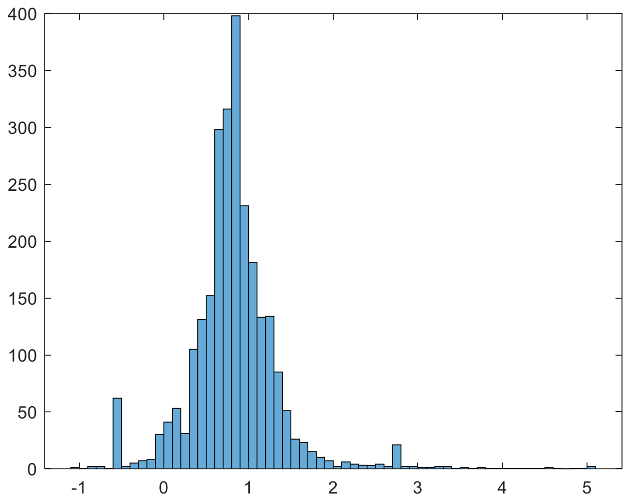


Figure 3b: Leveraged betas

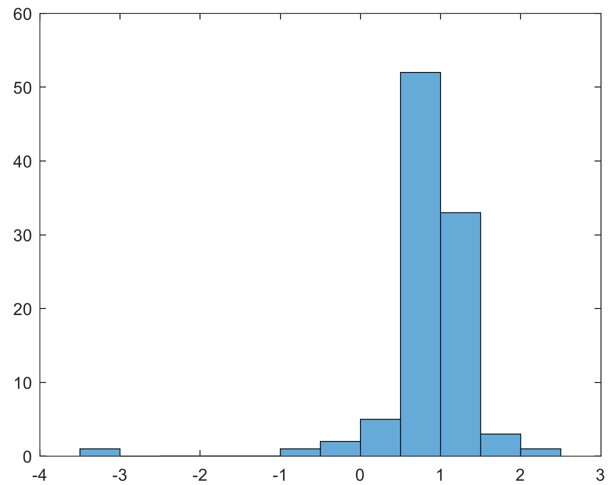
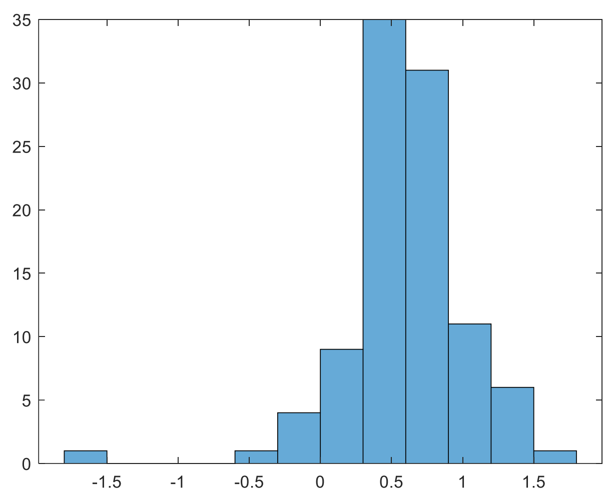


Figure 3c: Leveraged and De-smoothed betas



Note: The figure plots the distribution of MSA betas in the robustness test. Panel A is based on the time varying rolling window MSA betas. Panel B is leveraged NACRIEF MSA returns and national returns. Panel C is based on the desmoothed leveraged NACRIEF MSA returns and national returns.

We also apply previous robustness tests on the two groups of REITs (Appendix 2). The results are very robust. With the increase in the concentration of assets, REITs become more vulnerable to location risks. 33% of the most concentrated firms have the highest sensitivity to local beta.

4.4 Portfolio Construction and Non-Market Returns

We examine the non-market returns (or alphas) on REITs portfolios using an asset pricing model:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}LIQ_t + \beta_{p,6}RE_t + \varepsilon_{p,t}, \quad (18)$$

where $r_{p,t}$ is the equally-weighted monthly return on a given portfolio and $r_{f,t}$ is the corresponding risk-free rate as measured by the yield on the 1-month Treasury bill. We use two sets of factors. The first set are the two Fama–French factors (SMB and HML), the Carhart momentum factor (MOM) and the Pastor and Stambaugh liquidity factor (LIQ), in addition to the stock market return index (MKT). The second set is real estate factors to control for real estate market exposure. For this purpose, we also include listed real estate returns (NAREIT).[12]

The regressions are based on portfolios of REITs' monthly returns between 1998 and 2015. The baseline results present four sorted portfolios, from the bottom 25th percentile of REITs with the highest location risks and the upper 25th percentile of firms with the lowest location risks. Table 5 reports alpha and beta for each portfolio based on Equation (14). Among the six factors, the stock market factor has the highest sensitivity. The beta coefficient is close to one. Size factor and high minus low factor also play a role in the portfolio returns. The real estate factor, NAREIT returns, plays a limited role. This might be caused by the fact that NAREIT returns are highly correlated with the stock market return.

Although none of the alphas of the four portfolios is significant, the alpha for the portfolio based on taking the long position of REITs with highest local beta and taking the short position of REITs with the lowest local risk *is* significant. If investors perceive a higher risk in REITs subject to higher real estate risks, we would expect a higher return on portfolios with a high exposure relative to those with low exposure. In other words, portfolio managers with an information advantage are able to "buy low" before positive information has been incorporated into asset valuations and "sell high" before negative information has been fully reflected into falling asset prices. Firms with the

[12] Alternatively, we also used the NCRIEF total return indicator as an additional measure for real estate market performance; the results remain robust. However, the beta for NCREIF total return index is significantly negative, which might be caused by the multicollinearity between NCRIEF returns, NAREIT returns and stock market returns.

25th quantile highest local beta experience an average monthly non-market return of –0.16%. Firms with the 25th quantile lowest local beta experience an average return of -0.67%. This implies 50 basis point monthly (6% annually) return difference, which is statistically and economically significant.

Table 8: Portfolios Based on Local Beta

Note: This table presents factor model results of portfolios sorted into four groups from the bottom to the top 25th percentile based on the local beta. Alpha stands for non-market return. MR stands for the return factor, SMB stands for the size factor, HML stands for the book-to-market value factor, MOM stands for the momentum factor and LIQ stands for the liquidity factor. RE stands for the listed real estate returns. The portfolios are constructed based on monthly data. The T-statistic is reported in parentheses. ***,** and * denote significance at the 1%, 5% and 10% level, respectively.

Portfolio	Alpha	MR	SMB	HML	MOM	LIQ	RE	R2
Panel A Portfolio formed based on Location risk								
Highest	-0.0016	1.0025***	0.6253***	0.4564***	0.4993***	-0.0773	0.0871***	0.5447
	(-0.4505)	(10.8762)	(4.7754)	(3.6860)	(3.0061)	(-0.8044)	(2.0817)	
	-0.0036	1.0557***	0.6985***	0.4296***	0.5341***	-0.1923*	0.0722	0.5164
	(-0.9217)	(10.4367)	(4.8608)	(3.1615)	(2.9303)	(-1.8228)	(1.5736)	
	-0.0045	0.9369***	0.6277***	0.4548***	0.5825***	-0.1539	0.0638	0.4580
	(-1.1321)	(9.2100)	(4.3431)	(3.3282)	(3.1781)	(-1.4499)	(1.3807)	
Lowest	-0.0067	1.0704***	0.6506***	0.3593***	0.7283***	-0.1882*	0.1030***	0.4656
	(-1.5904)	(9.9267)	(4.2469)	(2.4804)	(3.7482)	(-1.6729)	(2.1053)	
Panel B: Portfolio long in firms with the highest local beta and short in firms with the lowest local beta								
Long H short	0.0050**	-0.0679	-0.0253	0.0971	-0.2290**	0.1108*	-0.0160	0.0394
L Portfolio	(2.0498)	(-1.0713)	(-0.2805)	(1.1399)	(-2.0044)	(1.6757)	(-0.5542)	

We further double-sort the portfolios according to diversification and location risk. REITs are first grouped into 50% REITs with more concentrated assets (50% highest HHI or lowest number of MSAs) and the rest. We then construct four equally-weighted portfolios for each group of REITs, from the bottom 25th percentile of firms with the highest location risks to the upper 25th percentile of firms with the lowest location risks. As shown in Table 8, a significant difference in the alpha between a portfolio with the highest and lowest exposure to location risks only occurs in REITs with more concentrated assets, confirming the regression results in the previous section. For REITs with geographically well-diversified assets, there is no significant difference in alpha. Location risks are priced in REIT returns, but only for REITs with concentrated assets. For the 50% REITs with the highest HHI and the 25th quantile lowest local beta show an average non-market return of -0.75% p.m, which is statistically significant. The difference in the alphas rises to 0.95% percent p.m (ca. 12% p.a.).

Table 9: Portfolios Based on Local Beta: Diversification

Note: This table presents the factor model results of portfolios sorted into 8 groups from the bottom to the top 25th percentile based on the local beta and from the bottom to the top half REITs based on diversification. Alpha stands for non-market return. MR stands for the return factor, SMB stands for the size factor, HML stands for the book-to-market value factor, MOM stands for the momentum factor and LIQ stands for the liquidity factor. RE stands for the listed real estate returns. The portfolios are constructed based on monthly data. The T-statistic is reported in parentheses. ***,** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: HHI						
	Local Beta	**High**			**Low**	**H-L**
HHI	**High**	0.0009	-0.0039	-0.0084*	-0.0075*	0.0093***
		(0.25)	(-0.98)	(-1.66)	(-1.93)	(2.57)
	Low	-0.0059	-0.0060	-0.0020	-0.0054	-0.0038
		(-1.44)	(-1.28)	(-0.49)	(-1.09)	(1.43)
	H-L	0.0068***	0.0020	-0.0063*	-0.0021	
		(2.41)	(0.65)	(-1.71)	(-0.71)	
Panel B: Number of MSAs						
	Local Beta	**High**			**Low**	**H-L**
Num	**High**	-0.0050	-0.0055	-0.0016	-0.0073	-0.0034
MSA		(-1.02)	(-1.04)	(-0.35)	(-1.31)	(-0.97)
	Low	-0.0001	-0.0040	-0.0067	-0.0020	0.0066*
		(-0.03)	(-0.86)	(-1.23)	(-0.45)	(1.78)
	H-L	-0.0049	-0.0015	0.0052	-0.0053*	
		(-1.19)	(-0.48)	(1.44)	(-1.67)	

5 Conclusion

This paper studies the role of geography on equity performance from the point of location risks. By studying the real estate firms, we confirm the real estate channel proposed but not empirically supported by Tuzel and Zhang (2017). For a firm with high exposure to risky real estate markets, the value of its underlying assets would respond more strongly to the aggregate shock than a firm with low exposure to risky markets. Therefore, the equity return of this firm would be higher, as investors would require a higher reward due to the perceived a higher equity risk. The location risk is measured by local beta, which reflects the systematic risk of the underlying real estate markets where properties are located. The empirical results confirm a higher equity return for a firm with a higher location risk, mainly for firms with concentrated assets. On average, a one standard deviation increase in the local beta will result in a 1.2% increase in REIT equity returns. But for REITs with more diversified assets, the relationship between REIT returns and local beta becomes insignificant. The results remain robust when the issues concerning self-selection, leverage and valuation smoothing are corrected.

This paper has several implications. First, it helps real estate investors, pension funds and multi-asset managers to characterise the nature of risk/return of REITs. REITs show much lower sensitivity to stock market risks and a more positive sensitivity to local real estate risks as compared to general industrial firms. Tuzel and Zhang (2017) documented two competing channels – the wage hedging channel and the real estate channel – which predict a completely opposite relationship between equity return and local risks. Tuzel and Zhang (2017) show that most industrial firms follow the wage hedging channel, while this study confirms the real estate channel for REITs. As a result, REIT returns would respond positively to local shocks, while the equity returns of general industrial firms would not react to the real estate shocks. Therefore, given the different response to the real estate risks, REITs can be considered as an alternative investment vehicle to general stocks in multi-asset portfolios.

Although U.S. REITs are characterized by geographical well-diversified, investors should be aware that location risk has still been priced in REIT returns. Therefore, location risk may not be diversified by holding REITs with geographically overlapped assets. Besides, investors can optimise the mix of REITs according to their exposure to risky real estate markets using a "smart local beta" strategy. An investment strategy which sells REITs with high exposure to high beta areas and buys high exposure to low beta areas can earn a non-market return of nearly 6% per year.

Furthermore, by touching on the being local versus diversified debate, this project can also help individual REITs to understand the costs and benefits of being local. The empirical study shows that geographic diversification can reduce location risk. One would thus expect lower equity returns due to reduced location risks and thereby reduced equity risk. Concentrated REITs are more seriously subject to location risks. For 33% of the most concentrated REITs, a one standard deviation increase in the location risks will be related to a 5.4% increase in REIT returns and, by implication, in the required cost of equity.

Appendix 1: Alternative Estimate of Local Beta

Note: This table reports the results of Fama–MacBeth cross-sectional regression. The dependent variable is the annual excess return netting of the T-bill rate. . $r^{REIT}_{firm,t-1}$ is the lagged return. $\beta^{RE\ local}_{firm,t-1}$ stands for the lagged local beta for firm i. $\beta^{Stock\ Mrkt}_{firm,t-1}$ is for the lagged stock market beta. $\beta^{SMB}_{i,t-1}$, $\beta^{HML}_{i,t-1}$, and $\beta^{MOM}_{i,t-1}$ are the beta for Fama–French factors. Control variables include headquarter MSA beta, net operating income (NOI), G&A expenses (GA), change in market value, debt to equity ratio, market to book ratio, real estate investment growth and property type dummy. Standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Model A1: Size weighted	Model A2: Adjusted cost weighted
$\beta^{RE\ local}_{firm,t-1}$	0.1340***	0.1593**
	(0.0242)	(0.0691)
$\beta^{Stock\ Mrkt}_{firm,t-1}$	0.0248	-0.0024
	(0.0369)	(0.0477)
$r^{REIT}_{i,t-1}$	-0.1206***	-0.1287***
	(0.0142)	(0.0234)
Change in Size	4.5858***	4.5266***
	(1.2641)	(1.3704)
Market to	0.0460***	0.0436***
Book	(0.0073)	(0.0071)
RE Investment Growth	-0.0998***	-0.1904***
	(0.0031)	(0.0099)
Debt to Equity	-0.0084***	-0.0070**
	(0.0020)	(0.0032)
MSA_Ump	0.0014	-0.0120
	(0.0086)	(0.0146)
Property Type Dummy	Yes	Yes
No. of obs	911	968
Adj. R2	0.7818	0.8095

Appendix 2: Diversification and Location Risk – Robustness Tests

Note: This table reports the results of Fama–MacBeth cross-sectional regression. The dependent variable for Model 14 and 19 is the local beta. The dependent variable from Model 15 to 18 and from Model 20 to 23 is the annual excess return netting of the T-bill rate. $\beta_{firm,t-1}^{RE\ local}$ stands for the lagged local beta for firm i. Control variables include the previous return, stock beta, change in market value, debt to equity ratio, market to book ratio, real estate investment growth and property type dummy. Standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	concentrated HHI>0.14	diversified HHI<=0.14	concentrated HHI>0.25	diversified HHI<=0.25
Panel A: Instrumented weights				
$\beta_{firm,t-1}^{RE\ local}$	0.3310***	0.0103	0.5244***	0.1755
	(0.1068)	(0.0516)	(0.1582)	(0.2024)
No. of obs	560	714	397	877
Adj. R2	0.7967	0.8492	0.8786	0.7873
Panel B: Instrumented weights_SigFtest				
$\beta_{firm,t-1}^{RE\ local}$	0.4751***	-0.4725	0.5202**	-0.1867
	(0.1639)	(0.9039)	(0.2645)	(0.2611)
No. of obs	369	270	273	366
Adj. R2	0.7669	0.9120	0.7569	0.8952
Panel C: Instrumented weights__Heckman				
$\beta_{firm,t-1}^{RE\ local}$	0.2375**	0.2013	0.4291**	-0.0659
	(0.1330)	(0.3663)	(0.2086)	(0.2489)
No. of obs	344	266	243	357
Adj. R2	0.8114	0.2037	0.8097	0.8528
Panel D: Time Varying MSA Beta				
$\beta_{firm,t-1}^{RE\ local}$	0.3188**	0.0249	0.3857***	0.0174
	(0.1500)	(0.0425)	(0.1479)	(0.1078)
No. of obs	515	639	369	785
Adj. R2	0.8944	0.8858	0.9477	0.8596
Panel E: Sector MSA Beta				
$\beta_{firm,t-1}^{RE\ local}$	0.1096**	-0.0180	0.2817***	0.0127
	(0.0500)	(0.0480)	(0.0694)	(0.0722)
No. of obs	514	644	369	789
Adj. R2	0.8723	0.8698	0.9364	0.8095
Panel F: leveraged and desmoothed MSA beta				
$\beta_{firm,t-1}^{RE\ local}$	0.2933***	-0.1122	0.3063***	0.0093
	(0.0697)	(0.1587)	(0.0636)	(0.0536)
No. of obs	221	301	156	358
Adj. R2	0.9183	0.9550	0.9679	0.9188
Panel G: Excluding Negative Beta				
$\beta_{firm,t-1}^{RE\ local}$	0.2997***	-0.1088	0.3691***	0.0579
	(0.1022)	(0.0832)	(0.0984)	(0.1038)
No. of obs	511	633	369	775
Adj. R2	0.8083	0.8398	0.9047	0.7590

Panel H: Using GDP shock				
$\beta_{firm,t-1}^{RE\ local}$	0.1370**	0.0154	0.1260**	0.0484**
	(0.0537)	(0.0474)	(0.0564)	(0.0248)
No. of obs	519	661	374	806
Adj. R2	0.8119	0.8617	0.8985	0.7883
Panel I: Excluding 2007-2015 in local beta calculation				
$\beta_{firm,t-1}^{RE\ local}$	-0.1211	-0.0962	0.1177**	-0.0429
	(0.1361)	(0.0687)	(0.0637)	(0.1280)
No. of obs	491	532	360	663
Adj. R2	0.8094	0.8385	0.8903	0.7997
Panel J: Excluding 2007-2015 in returns				
$\beta_{firm,t-1}^{RE\ local}$	0.2270***	-0.0380	0.9084***	0.2231**
	(0.0368)	(0.0894)	(0.1039)	(0.1234)
No. of obs	186	292	136	342
Adj. R2	0.3640	0.8017	0.7448	0.6082

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