DOI: 10.1111/1540-6229.12402

ORIGINAL ARTICLE

WILEY

Industrial tail exposure risk and asset price: Evidence from US REITs

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June 6, 2022

Abstract

In this study, we investigate the impact of industry-based tail dependence risk on the cross-section of stock returns. To this end, we propose a novel tail risk dependence measure (industrial tail exposure risk [ITER]), which captures the tail risk exposure of individual stocks to multiple industries. Using US equity real estate investment trusts (REITs) data from 1993 to 2020, we document that stocks in the highest ITER portfolio outperform stocks in the lowest ITER portfolio by 8.40% per annum. This positive return spread is significant even after controlling for well-known firm characteristics. The return premium of ITER is stronger for small, value, and highly levered stocks and is substantially high during recession periods. Finally, the effects of ITER are cross-sectionally more associated with REITs that have greater degrees of the following factors: bivariate tail exposure risks of major industries, exposure to local industry tail risk, geographical concentration, and ownership of home-biased investors. Overall, our results suggest that REIT investors are indeed averse to tail risks that are associated with various sectors.

KEYWORDS
asset price, cross-section of returns, real estate investment trusts (REITs), risk aversion, tail dependence, tail risk

JEL CLASSIFICATION
C12, G01, G11, G12, G17

1 INTRODUCTION

It has been firmly established that individuals are averse to extreme tail events and want to hedge against a sharp drop in their assets (Kahneman & Tversky, 1979; Menezes et al., 1980; Roy, 1952). Risk-averse investors require return premiums as compensation from stocks that have shown stronger sensitivities to tail events because these stocks could have a higher probability of wealth destruction in investment portfolios. Several empirical asset pricing studies have investigated the impact of tail risk on expected future returns and documented mixed findings (e.g., Chabi-Yo et al., 2018; Kelly & Jiang, 2014; Van-Oordt & Zhou, 2016). These studies measure tail dependences in returns between individual stock and the aggregate market return. However, tail dependencies with market return suffer a limitation of observations for the measurement because there are only a few aggregate tail events in the history of the stock market. Furthermore, previous studies have not explored tail dependencies that are associated with tail events from more specific sources than the aggregate economy. This article bridges this gap by proposing a novel tail risk measure, which we call industrial tail exposure risk (ITER). This tail risk measure incorporates multiple bivariate lower tail dependencies between individual firms and other sectors. We exploit firm-level ITER to examine whether there is a tail risk premium in the cross-section of future expected returns.

We exploit the publicly listed equity real estate investment trust (REIT) market as a laboratory to test the empirical hypothesis of tail risk premiums from multiple industries.[1] The unique structure of REITs allows us to obtain industry-based tail dependence measures. First, a vast majority of assets of REITs are real estate, which is significantly dependent on various industries through local market channels (e.g., Tuzel & Zhang, 2017). Suppose that certain sectors play a crucial role in a particular local market economy. In this area, extremely negative productivity shocks of dominating sectors should be transmitted to local firms, laborers, and households (e.g., Dougal et al., 2015). These shocks then trigger downward pressures on the performance of local real estate. This suggests that REITs could be exposed to the extreme downside risk of other industries if the REITs hold a considerable portion of their real estate in a particular region. In addition, REITs have tenants belonging to various industries. REITs generate most of their operating income from tenants. Thus, the downside risk of tenants is directly associated with the performance of REITs. For instance, a collapse of a particular industry could transmit idiosyncratic shocks to REITs if the REITs are significantly exposed to tenants of this industry. This tenant risk could be more substantial if REITs are specialized in particular sectors, such as hotels, health care, shopping centers, data centers, and so forth. For example, the 9/11 terrorist attack prompted severe uncertainties in the accommodation industry, generating a much larger loss in the hotel sector of the REIT market.

[1] The public REITs are stocks that based on companies holding income-producing real estate or mortgage products and providing dividends and capital gains to stockholders.

Therefore, we exploit the US equity REITs to measure the tail dependences between individual stocks and multiple sectors. This industry-based tail dependence risk could not be captured if we rely on bivariate tail dependence between REIT and the aggregate market, which has been widely explored by previous studies (e.g., Chabi-Yo et al., 2018; Van-Oordt & Zhou, 2016). The time-varying economic activity of the whole market cannot explicitly provide the extreme downturn of certain industries unless the market is under a nationwide recession. For example, the aggregate market returns would not reflect crash events of particular industries if other industries perform well during the same period. In other words, extremely negative returns of some industries can be offset by other industries with strongly positive returns under the aggregate market. Thus, it is crucial to incorporate tail risk information from multiple industries rather than the aggregate economy.

To this end, we develop a novel methodology that combines multiple tail dependencies between REITs and Fama–French 12 value-weighted industries into one composite information. Specifically, we estimate a firm-level ITER using the joint distribution of lower-tail returns between individual REITs and 12 industries. Based on a 3-year rolling window estimation from daily return data for US equity REITs and Fama–French 12 industries between 1993 and 2020, we first obtain 12 bivariate tail exposure risks (BTERs) between REITs and 12 other industries. Then, we employ PCA to incorporate these BTERs into one composite index (first component), which we call "ITER."

We use residual returns relative to Carhart's (1997) four factors to estimate ITER. There are several reasons for using idiosyncratic components to measure tail dependence rather than raw returns for REITs and industries. First, idiosyncratic risk matters in a not completely diversified portfolio. Different from traditional asset pricing models, previous studies have documented that investors cannot operate a fully diversified portfolio (Merton, 1987; Xu & Malkiel, 2003) and that underdiversified portfolios are sensitive to extreme downside risks (Dimmock et al., 2021). Importantly, retail investors are more involved in underdiversified portfolios (Polkovnichenko, 2005). As REITs are held by many individual investors due to the "five or fewer" rule, idiosyncratic risk could be an important factor.[2] Second, industry-specific shocks are important components of the cross-sectional asset price of REITs in the context of the local economy. Recent studies show that sectoral tail risk could give rise to macroeconomic tail risk (Acemoglu et al., 2017; Gabiax & Koijen, 2021). This effect can be more evident when the aggregate economy is decomposed into a more granular regional economy where fewer industries dominate local factors (e.g., Tuzel & Zhang, 2017). Given that at least 75% of REITs' assets are real estate, which is significantly governed by the local economy, idiosyncratic sector-level shocks could be an important source of risk. Finally, yet importantly, raw returns contain a systematic component, which could lead to spurious tail dependence between the REIT and industry because the source of tail dependence might be driven by aggregate shocks rather than industry-specific shocks.

Using the ITER measure, we conduct various empirical asset pricing tests to investigate whether ITER has a positive intertemporal relationship with the expected future returns of REITs. Overall, our empirical results show that REITs with higher ITER have stronger future returns than REITs with lower ITER. From univariate portfolio analysis, we find that REITs in the highest ITER group (Quintile 5) provide significantly higher future average returns of 0.70% per month (8.40% per annum) than REITs in the lowest ITER group (Quintile 1). This return spread is consistently

[2] "Five or fewer" rule prohibits five or fewer shareholders from owning over 50% of the total shares in a REIT (see Capozza & Seguin, 2003).

positive and highly significant in alphas relative to well-known factor models: Sharpe's (1964) capital asset pricing model (CAPM), Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model. The positive alpha remains highly significant even after controlling for various combinations of risk factors on top of the Carhart four-factor model. Furthermore, the return premium is positive and statistically significant after controlling for macroeconomic and various systematic risk factors. We further investigate whether the return premium of ITER is distinguished from other firm-specific risk factors. From the results of the bivariate portfolio analysis, we find that the impact of ITER remains consistently positive after controlling for illiquidity (Amihud, 2002), beta (Shapre, 1964), coskewness (Harvey & Siddique, 2000), and cokurtosis (Dittmar, 2002; Fang & Lai, 1997). In addition, we examine whether the impact of ITER varies with firm characteristics. We document that small, value, and highly levered stocks are more significantly priced by ITER.

To ensure that the return premium of ITER is consistent under multiple control variables, we conduct Fama–MacBeth (1973) cross-sectional regression. From the regression results, the slope coefficient of ITER is positive and highly significant, with a Newey–West t-statistic of 3.91, which exceeds the standard level t-statistic (3.0) suggested by Harvey et al. (2016). The coefficient estimate of 0.14 indicates a return spread of 0.68% per month in average returns between the first and fifth quintiles of ITER. Our ITER also has strong predictive power in the long-term horizon. The results from predictive cross-sectional regression show that the coefficient of ITER is positive and statistically significant for at least the next 12 months.

We further examine whether the tail risk premium varies with market conditions. Theoretical literature has demonstrated that risk aversion is time-varying (e.g., see Barberis et al., 2001; Campbell & Cochrane, 1999). In particular, the risk aversion of investors is significantly higher during turbulent periods (e.g., Chen et al., 2012; Guiso et al., 2018). Consistent with the theoretical prediction, we find that the ITER premium shows a countercyclical movement. The slope coefficient of ITER increases substantially during the 2008–2009 economic recession when the risk aversion of investors would be substantially larger than in other periods. In addition, we demonstrate that the coefficients of our ITER measure capture a more significant impact of risk aversion than that of the market beta, which is the classical measure of firm-level systematic risk. We also document that the economic magnitude of the ITER coefficient is much larger during the National Bureau of Economic Research (NBER) recession periods.

Finally, to understand the effects of ITER, we explore the methodological characteristics of ITER and various characteristics of REITs. We find that the cross-sectional ITER premium is more associated with REITs that have higher BTER with major industries. This finding is in line with the recent finding that industry should be sufficiently dominant to trigger extreme risk at the macroeconomic level (e.g., Acemoglu et al., 2017). In addition, the predictability of ITER is stronger for REITs with larger geographical concentrations and exposure to the higher tail risk of local industries. This suggests that investors require more premiums from REITs that have difficulty in the diversification of risk due to local concentration and increased regional risk. Finally, in line with the geographical segmentation literature (e.g., Coval & Moskowitz, 1999, 2001), REITs with higher exposure to home-biased investors are more strongly related to the ITER premium.

Our article relates to the literature on asset prices associated with downside risk. Downside risk aversion has been one of the fundamental areas since Roy (1952). This loss aversion is also a major mechanism of the "risk-return tradeoff" in which risk positively varies with the expected return. Risk aversion has been documented throughout various models (Gul, 1991; Kahneman & Tversky, 1979; Markowitz, 1959; Merton, 1973; Routledge & Zin, 2010; Roy, 1952, among many others). Roy (1952) introduced the notion of "safety first" to explain the risk aversion of agents. Using utility theory, he argues that the level of disaster risk can be adjusted according to the expected compensation when disaster risk is not independent of the expected outcome. Merton (1973) derived the intertemporal CAPM, in which the conditional variance of return at time t is positively correlated with the expected excess return time $t+1$ conditioning on the information set at time t. Kahneman and Tversky (1979) alternatively suggested "prospect theory" to explain risk aversion. They note the behavioral feature of individual overweighting on the loss side relative to gains in the framework of a utility function. The relation between rare disaster risk and asset price has recently received significant attention in the literature (e.g., Barro, 2006, 2009; Chen et al., 2012; Wachter, 2013). For example, Barro (2006) documented that the probability of a market crash addresses risk premium puzzles in asset returns. Chen et al. (2012) derived the time-varying feature of disaster risk premium in the sense that the level of compensation is positively correlated with market depression when the share of optimists decreases. Wachter (2013) found that the time-varying likelihood of a potential consumption disaster explains not only the equity premium but also the high volatility of the stock market.

On the motivation from a theoretical background, several empirical studies have investigated the impact of tail risk on the cross-section of stock returns. (Agarwal et al., 2017; Bollerslev et al., 2015; Chabi-Yo et al., 2018; Karagiannis & Tolikas, 2019; Kelly & Jiang, 2014; Van Oordt & Zhou, 2016). For instance, Kelly and Jiang (2014) mainly contributed to this literature strand by proposing a novel aggregate tail risk methodology based on Hill's (1975) estimator. They extract the typical fluctuation of tail risk from the lower tail distribution using a dynamic power-law structure (Gabaix & Ibragimov, 2011; Gabaix et al., 2006). They find that stocks having stronger comovement with aggregate tail risk provide significantly higher annual three-factor alpha. Karagiannis and Tolikas (2019) adopted Kelly and Jiang's (2014) approach and found the tail risk premium in the cross-section of mutual fund returns.

Overall, various forms of risk and tail risk have been exploited to investigate the cross-sectional feature of return. Previous literature generally focuses on the individual stock's sensitivity to aggregate level tail risk in explaining the asset price. Only a few studies focus on firm-level tail risk exposure. Agarwal et al. (2017) adopted a systemic tail risk based on expected shortfall (ES) and documented that significant cross-sectional variation in fund returns is correlated with systemic tail risk. Van Oordt and Zhou (2016) developed systematic tail beta using extreme value theory and find no evidence of systematic tail risk premium in the cross-section of returns. Chabi-Yo et al. (2018) empirically demonstrated the "crash-aversion" by using lower-tail dependence based on copulas. These studies consider the bivariate dependence structure between individual stock and market-level returns. This bivariate tail dependence approach using aggregate market returns might lose important information about firm-specific downside risks associated with industry exposures. However, previous studies have not explored the asset pricing implication of tail risks from various industries, apart from the aggregate market risk. This study bridges this gap by examining asset pricing implications based on the tail dependence between individual firms and various industries. To the best of our knowledge, our study is the first to investigate the tail risk premium using return information from multiple sectors.

The rest of the article is organized as follows. Section 2 explains the methodology for estimating ITER. Section 3 describes the data, variables, and summary statistics. Section 4 presents the results of various empirical asset pricing tests. Section 5 concludes this article.

2 | METHODOLOGY

Our goal in this section is to obtain the ITER, which incorporates multiple BTERs between individual REITs and industries. We first estimate BTER using the joint tail distribution of bivariate pairs between REIT and other industries. We then apply PCA to obtain the first principal component from multiple BTERs. We use the first principal component as ITER to examine the tail risk premium in the main analysis section. In the estimation, we exploit daily stock returns to obtain more sufficient observations of joint left-tail events.

2.1 | BTER

In the first step, we apply a 36-month rolling window estimation to measure the BTER between REIT and industry. Specifically, we measure the crash sensitivity of individual REITs by focusing on days when both REIT and industry fall into the left-tail of the return distribution. Suppose that there are REIT i and industry j among N industries and the rolling window period has n daily observations. In the classical methodology, bivariate tail dependence between REIT return r_i and industry return r_j is defined as follows:

$$TD_{i,j} = \lim_{q\to 0} P(r_i < VaR_i(q)\,|r_j < VaR_j(q)) = \lim_{q\to 0} \frac{P(r_i < VaR_i(q), r_j < VaR_j(q))}{P(r_j < VaR_j(q))}, \tag{1}$$

where $VaR_i(q)$ ($VaR_j(q)$) indicates the value-at-risk (VaR) threshold of the return of REIT i, r_i (return r_j of industry j) with a q probability level. TD is the tail dependence, which denotes the probability of an extremely low return realization of r_i conditional on an extremely low return realization of r_j. This bivariate tail dependence measure has been utilized to investigate the financial contagion effect (e.g., Boyson et al., 2010; Longin & Solnik, 2001), asset market linkage (e.g., Hartmann et al., 2004), and return predictability (e.g., Agarwal et al., 2017). However, the classical tail dependence measure does not reflect the feature of the heavy-tailed return distribution. Thus, we exploit the tail dependence measure of Van Oordt and Zhou (*VZ*; Van Oordt and Zhou, 2019), $TD_{i,j}^{VZ}$, which addresses the potential estimation problem:

$$TD_{i,j}^{VZ} \equiv TD_{i,j}^{\frac{1}{\xi_j}}, \tag{2}$$

where $\frac{1}{\xi_j}$ is the tail index of the industry return r_j under the heavy-tailed distribution assumption.[3] $TD_{i,j}^{VZ}$ can be estimated by applying well-established Extreme Value Theory (EVT) estimators using the elements as follows:

$$\widehat{TD}_{i,j}^{VZ} = \widehat{TD}_{i,j}^{\frac{1}{\hat{\xi}_j}}, \tag{3}$$

[3] We assume that the empirical distribution of equity return is heavy-tailed, which has been established since Mandelbrot (1963) and Fama (1963) and further documented by Embrechts et al. (2013).

$$\widehat{TD}_{i,j} = P(r_i < \widehat{VaR}_i(m/n) | r_j < \widehat{VaR}_j(m/n)), \tag{4}$$

where $\widehat{VaR}_i(m/n)$ and $\widehat{VaR}_j(m/n)$ are the VaR thresholds estimated as the $(m+1)$th lowest return among n observations for the rolling window period. This suggests that m/n is a discrete expression of the probability q since the number of observations is finite. Thus, $\widehat{TD}$ can be estimated nonparametrically using the empirical distribution of r_i and r_j as in Embrechts et al. (2013) and Agarwal et al. (2017):

$$\widehat{TD}_{i,j} = \frac{1}{m}\sum_{i=1}^{m} I\left(r_i < \widehat{VaR}_i(m/n), r_j < \widehat{VaR}_j(m/n)\right), \tag{5}$$

where $I(X)$ is an indicator function taking a value of 1 for X or 0 for X^c. Thus, this measure denotes the probability of joint plunge of r_i and r_j during the rolling window period of n observations. The tail index $\frac{1}{\hat{\xi}_j}$ is estimated using Hill's (1975) estimator:

$$\frac{1}{\hat{\xi}_j} = \frac{1}{m}\sum_{i=1}^{m} \ln\frac{r_{j,n}}{u_n}, \tag{6}$$

where u_n is an extreme lower tail threshold for n observations, ($(m+1)$th worst loss among n observations of the industry return), $r_{j,n}$ is industry return that is lower than u_n, and m is the total number of observations exceeding the tail threshold u_n. This tail index estimator denotes the fatness of the tail distribution of industry return r_j. Based on the theoretical rule suggested by Gabaix et al. (2006) and empirical evidence documented by Kelly and Jiang (2014), we choose $m/n \approx 5\%$.

As the tail dependence only reflects the extremely lower tail linkage between REIT and a particular industry, we could not identify how severe the crash is for individual REIT when an extreme joint fall occurs between REIT and industry. Thus, we complement the bivariate tail dependence risk by further estimating the severity ratio of REIT to industry using ES based on a nonparametric approach:

$$SR_{i,j} = \frac{ES(r_i)}{ES(r_j)} = \frac{E(-r_i | r_i < VaR_i(q))}{E\left(-r_j | r_j < VaR_j(q)\right)}, \tag{7}$$

where $ES(r_i)$ and $ES(r_j)$ are the ES of the return of REIT i and industry j. In this study, we choose ES over VaR since ES exhibits better features for measuring risk, such as coherency (e.g., see Agarwal & Naik, 2004; Artzner et al., 1999; Liang & Park, 2007). Then, we can nonparametrically estimate $SR_{i,j}$ using the empirical distribution of r_i and r_j.

$$\widehat{SR}_{i,j} = \frac{\widehat{ES}(r_i)}{\widehat{ES}(r_j)} = \frac{\frac{1}{m}\sum_{i=1}^{m}(-r_i \; | r_i < \widehat{VaR}_i(m/n))}{\frac{1}{m}\sum_{i=1}^{m}(-r_j \; | r_j < \widehat{VaR}_j(m/n))}, \tag{8}$$

where $\widehat{VaR}_i(m/n)$ and $\widehat{VaR}_j(m/n)$ indicate the thresholds for ES estimated in (4). Finally, BTER between REIT i and industry j can be obtained as follows:

$$\widehat{BTER}_{i,j} = \widehat{TD}^{VZ}_{i,j} \times \widehat{SR}_{i,j}. \tag{9}$$

Based on the 36-month rolling window estimation, we obtain BTER ($\widehat{BTER}_{i,j,t}$) for each pair between REIT and industry at the end of every month.

One potential concern is that common return factors might bias the tail dependence measures. In addition, McNeil and Frey (2000) emphasize the better statistical feature of applying residuals to the extreme risk measures than raw returns in that residuals show approximately independence over time. In addition, the residual returns relative to common market risks have been frequently exploited in empirical EVT literature (e.g., see Huang et al., 2012). Thus, we remove common risk factors from excess returns of individual REIT and industry and extract residuals using Carhart's (1997) four-factor model:

$$r_t - r\,f_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{HML}MOM_t + \varepsilon_t, \tag{10}$$

where $r_t - rf_t$ indicates the daily excess return of REIT or industry; rf_t is the 1-month Treasury bill (T-bill) rate measured by the 1-month US Treasury bill; MKT_t is the market excess return; SMB_t, HML_t, and MOM_t indicate the returns based on the portfolio of size, BM, and momentum, respectively; and ε_t represents residuals of REIT or industry.[4] Since market risk exposure is time-varying, as confirmed in Fama and French (1997) and Lewellen and Nagel (2006), we obtain residuals for every rolling window estimation to estimate the BTER. This process allows us to obtain $\widehat{BTER}_{i,j,t}$ that does not contain first-order time-varying market risk factors.

2.2 | ITER

Based on BTER ($\widehat{\mathrm{BTER}}_{\mathrm{i,j}}$), we finally estimate the ITER, which indicates a firm-level tail risk exposure to other industries. To this end, we incorporate N number of $\widehat{BTER}_{i,j}$ into one index, $\widehat{ITER}_i$, by extracting the first principal component from PCA.[5] PCA has recently received attention for its ability to generate composite variables from various factors. The studies include the sentiment index by Baker and Wurgler (2006), the macroeconomic risk by Bali et al. (2014), and the macroeconomic uncertainty by Jurado et al. (2015)).

For the industries exploited in the estimation, we use Fama–French 12 value-weighted industry returns. Our choice of industry classification is motivated by one concern. If we choose too few classified industries, our ITER measure cannot differentiate itself from tail exposure risk, which depends on only aggregate market returns. On the other hand, if we use too many classified industries, the first principal component may lose explanatory powers. Thus, we choose Fama–French 12 industries, which could balance the tradeoff. However, we check the robustness of our results using different industrial classifications by Fama and French.

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[4] We obtain Carhart four factors and 1-month risk free rate from Kenneth French's website at http://mba.tuck.-dartmouth.edu/pages/faculty/ken.french/data_library.html.

[5] ITER could be estimated using a joint distribution of individual REIT and 12 industries (multivariate dependence based on 18 returns). However, this approach provides very few observations since it should be an infrequent event when all of the returns simultaneously fall below 5% threshold.

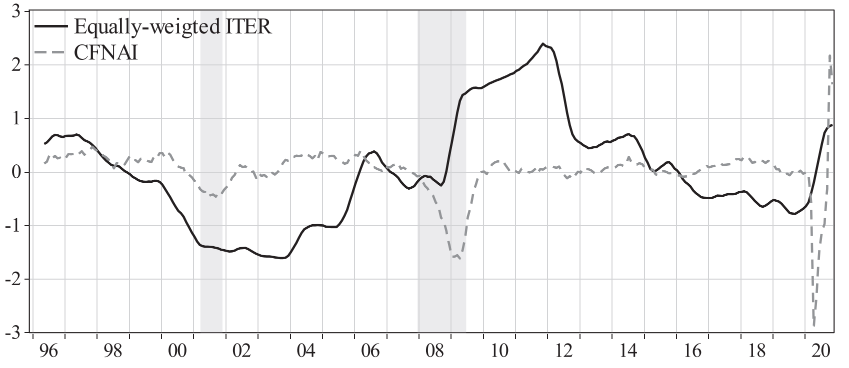

FIGURE 1 Monthly industrial tail exposure risk (ITER) measure over time

Note: The figure presents the evolution of equally weighted ITER and 6-month moving average Chicago Fed National Activity Index (CFNAI) over the sample period from December 1995 to December 2020. Aggregate monthly ITER is obtained by an equally weighted method based on a monthly cross-section of individual ITER measures from real estate investment trusts (REITs). For comparison, two time series variables are standardized to have zero mean and one standard deviation. The shaded area indicates the NBER recession periods

As we use 12 industries, PCA generates up to 12 principal components, which are linear weighted factors of 12 $\widehat{BTER}_{i,j}$. Among 12 principal components, the first principal component is of our central interest since we use this component as ITER, which captures the first-order common time-series variation of 12 $\widehat{BTER}_{i,j}$. The first principal component in the cross-section of REITs, on average, explains 64.23% of the sample variance. Thus, we conclude that the first factor extracts sufficient information from the common variation among the 12 tail exposure risk factors. As we use 36-month daily returns to obtain monthly ITER, the set of ITER begins with the sample from January 1993 to December 1995 and ends with the sample from January 2017 to December 2020.

To explore the time-varying characteristics of aggregate ITER, we plot the evolution of equally weighted aggregate ITER and the 6-month moving average of Chicago Fed National Activity Index (CFNAI) in Figure 1.[6] For the comparison, we standardize two variables to have zero mean and one standard deviation. The time series of ITER fluctuates substantially over the sample period. In particular, we can find the historic spike that corresponds with the collapse of Lehman Brothers during the subprime mortgage crisis. This spike indicates that REITs tend to show numerous joint tail events with various industries during extremely volatile periods, although we extracted the first-order impacts of aggregate market factors.

3 | DATA

We use publicly listed US equity REITs during the new REIT era from 1993 to 2020. Daily values of stock return, trading volume, and market capitalization are collected from the Center for Research in Security Prices (CRSP). The REIT sample is compared with the equity REIT list of Feng et al. (2011) and the historical constituents list for the National Association of REIT (NAREIT) index on the website of NAREITs. Delisted REITs were included in the sample to avoid survivorship

[6] CFNAI is monthly index, which is constructed based on the weighted average of 85 monthly economic indicators.

bias. Individual REIT should have over 36 months for the rolling estimation. We further require REIT to have at least 50% of nonzero returns in the return distribution. In the final sample, there are 28,191 firm-month observations. The number of REITs each month varies between 49 and 120 over the sample period. The total number of REITs in our sample is 248.

We extract annual financial information from the COMPUSTAT and SNL REIT databases. For firm characteristics, we construct size (*SIZE*), book-to-market (*BM*), market leverage (*MLEV*), and return on equity (*ROE*). The size is estimated as the natural logarithm of market capitalization (product of share price and the number of shares outstanding) at the end of June of year t. The book-to-market is the ratio of common equity to the market value of equity. The leverage is based on market leverage estimated as the total debt (short-term debt plus long-term debt) divided by market value (total debt plus market capitalization). The return on equity is computed as the income before extraordinary items scaled by the total book asset. Following the approach of Fama and French (1992, 1993), we match the financial information at the end of fiscal year $t-1$ with CRSP stock return data from July of year t to June of year $t+1$, generating a period gap of at least 6 months between the period of fiscal year-end financial report provision and stock return.

We additionally construct several control variables, which are frequently used in the empirical asset pricing literature to assess risk premiums. First, following Amihud (2002), the illiquidity (*ILLIQ*) of REIT i at month t is computed as the monthly averaged value of the absolute daily return scaled by daily dollar trading volume:

$$ILLIQ_{i,t} = \frac{1}{N}\sum_{d=1}^{N}\frac{|r_{i,d}|}{VOLD_{i,d}}, \tag{11}$$

where N is the number of daily observations in month t, and $r_{i,d}$ and $VOLD_{i,d}$ are the daily return and the daily dollar trading volume (product of share price and the number of trading volume), respectively, for REIT i at day d. Second, we estimate Bali, Brown, Murray, and Tang (2017) *MAX* defined as an average of the five highest returns for the previous month to control for the demand for lottery-like stocks. Third, based on the motivation from Jegadeesh (1990), we use short-term reversal (*REV*), which is the stock return for the previous month. Fourth, the 1-year market beta is estimated using the CRSP value-weighted market return. Fifth, 1-year coskewness (*COSKEW*) and cokurtosis (*COKURT*) from Harvey and Siddique (2000) and Dittmar (2002), respectively, are obtained as follows:

$$COSKEW_{i,t} = \frac{E\left[(r_{i,t}-\mu_i)(r_{m,t}-\mu_m)^2\right]}{\sqrt{var(r_{i,t})}\,var(r_{m,t})}, \quad COKURT_{i,t} = \frac{E\left[(r_{i,t}-\mu_i)(r_{m,t}-\mu_m)^3\right]}{\sqrt{var(r_{i,t})}\,var(r_{m,t})^{\frac{3}{2}}}, \tag{12}$$

where $r_{i,t}$ and $r_{m,t}$ are the excess returns for REIT i and the market, respectively, and μ_i and μ_m are the average excess returns for REIT i and the market. Beta, $COSKEW_{i,t}$ and $COKURT_{i,t}$ are estimated over the 12-month period from $t-11$ to t. Last, past return (*PAST RET*) is obtained from the average past 12-month excess returns of REIT i at period t (Jegadeesh & Titman, 1993). All explanatory variables are winsorized at the 1% and 99% levels to rule out any influences driven by outliers.

TABLE 1 Summary statistics

	Mean	Standard deviation	P25	Median	P75	Low industrial tail exposure risk (ITER)	High ITER	High–Low
ITER	−0.026	2.442	−1.919	−0.383	1.525	−2.142	2.510	4.652***
Return (%)	0.832	9.644	−3.186	0.855	4.948	0.630	1.186	0.556**
SIZE	6.857	1.755	5.908	7.039	8.026	6.719	6.417	−0.302**
BM	0.708	0.496	0.421	0.604	0.837	0.675	0.838	0.164***
MLEV	0.425	0.186	0.306	0.410	0.539	0.413	0.457	0.044***
ROE	0.015	0.051	0.005	0.016	0.029	0.016	0.005	−0.012***
REV	0.954	7.917	−2.999	1.040	5.105	0.933	0.993	0.060
MAX	2.311	1.939	1.276	1.713	2.475	2.051	2.836	0.785***
PAST RET	0.864	2.441	−0.649	0.901	2.378	0.895	0.816	0.098***
ILLIQ	0.220	1.048	0.000	0.002	0.013	0.152	0.464	0.312***
BETA	0.678	0.494	0.290	0.584	0.988	0.630	0.741	0.111***
COSKEW	−0.127	0.247	−0.229	−0.081	0.037	−0.118	−0.110	0.007**
COKURT	2.235	1.930	1.017	1.853	2.933	2.174	2.014	−0.160***

Note: This table presents summary statistics for sample real estate investment trusts (REITs). The five columns show the mean, standard deviation, 25th percentile (p25), median, and 75th percentile (p75). ITER is obtained from the first principal component of 12 tail dependences between the daily return of respective REIT and 12 industrial portfolio returns over 36 months. Excess return is REIT return in excess of a one-month T-bill rate. Size is the natural log of market capitalization. Book-to-market (*BM*) is the ratio of the book value of equity to the market value of equity. *MLEV* (market leverage) is market leverage measured as the total debt (short-term debt + long-term debt) scaled by market value (total debt + market capitalization). *ROE* (return on equity) is obtained by income before extraordinary items divided by a total book asset. *ILLIQ* (Illiquidity) is a monthly averaged ratio of the absolute daily return to daily dollar trading volume. *MAX* is an average value of the five highest returns for the previous month. *REV* is short-term reversal, which is the stock return for the previous month. The market beta (*BETA*), coskewness (*COSKEW*), cokurtosis (*COKURT*), and past return (*PAST RET*) are obtained from the past 12-month daily return from $t-11$ to t.

3.1 | Summary statistics

Table 1 presents the descriptive statistics for firm characteristics and variables used in cross-sectional regressions. The first five columns show the mean, standard deviation, 25th percentile, median, and 75th percentile for all variables. The last two columns report the mean value of variables for the lowest and highest ITER portfolios based on five ITER quintiles. ITER shows a mean of −0.03 and has a substantial variation with a standard deviation of 2.44 and an interquartile range of 3.44. The mean excess return is 0.83%. The mean return for high ITER is 1.19, which is significantly higher than the mean return for low ITER. For firm characteristics, the average log firm size is 6.86, which is relatively higher than the 6.24 reported by Chung et al. (2016).[7] The book-to-market ratio (*BM*) is, on average, 0.71, reflecting that REITs show the feature of small value stock, which is consistent with Alcock and Andrlikova (2018). The mean market leverage is 43%, comparable with 46% over the 1990–2012 sample reported by Giacomini et al. (2017),

[7] Our sample period reflects recent REIT market capitalization up to 2020, while Chung et al. (2016) cover sample periods before 2010.

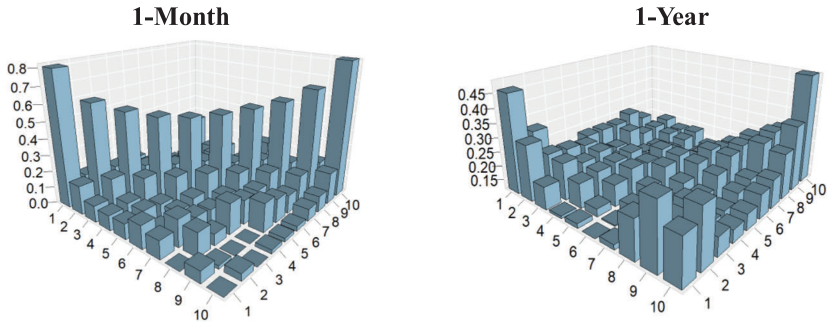

FIGURE 2 ITER transition matrix [Color figure can be viewed at wileyonlinelibrary.com]

Note: This figure displays the 1-month and 1-year portfolio transition matrix (i, j) in 3D histogram visualization. The transition proceeds from the left-bottom (i) to the right-bottom (j) axis. The 1-month and 1-year transition matrices reveal the frequency ratio of transition for REITs by month and year, respectively.

reflecting that REITs are highly levered. The summary statistics for other firm characteristics and return patterns are provided in the rest of the table. Overall, REITs with high ITER show significantly different firm characteristics from REITs with low ITER.

The correlation between the independent variables is presented in Table 2. ITER is relatively more correlated with beta (44%) and cokurtosis (27%), consistent with Van Oort and Zhou (2016), who document a strong positive relation between the downside tail dependence measure and market beta and cokurtosis. Following Alcock and Andrlikova (2018), we exploit the variance inflation factor (VIF) index, introduced by Belsley (1991), to test for any potential multicollinearity and find that there is no variable showing multicollinearity with a VIF above 5. We further check the robustness of the results using different sets of control variables in the multivariate analysis section.

3.2 | ITER persistence analysis

If the tail risk for individual REIT is persistent enough, investors will be likely to pay higher prices for low ITER REITs. Investors expect that these low ITER REITs will realize a similar pattern in the future, thereby hedging against extreme downside events. Thus, it is a natural question to examine whether the persistence of tail risk is sufficient to rationalize this expectation (Bali, Brown, & Tang, 2017). To this end, we construct a transition matrix for 10 decile portfolios based on ITER and visualize it in Figure 2 as in Chabi-Yo et al. (2018). Figure 2 shows a 1-month and 1-year transition matrix by 3D histograms. The value for (i, j) indicates the relative frequency of REIT sorted into ith decile portfolio in the month (year) t given that it was sorted into REIT jth decile portfolio in the month (year) $t-1$ over the sample period from December 1995 to December 2020. As shown in the figure, we find high persistence in ITER at both the 1-month and 1-year transitions. REITs sorted into first decile portfolio at month (year) $t-1$ remain in the same decile portfolio with a probability of 80.84% (46.08%). REITs sorted into the 10th decile portfolio at month (year) $t-1$ stay again in this 10th decile portfolio at 82.39% (49.40%). These results suggest that ITER sufficiently predicts future ITER and hence substantiate that investment expectations using past information of ITER can be viable.

TABLE 2 Correlation matrix between variables

Variables	*ITER*	*SIZE*	*BM*	*MLEV*	*ROE*	*ILLIQ*	*REV*	*MAX*	*BETA*	*COSKEW*	*COKURT*	*PAST RET*
ITER	1.000											
REV	−0.010	−0.010										
MAX	0.093	0.093	0.093									
MLEV	0.039	0.039	0.039	0.039								
ROE	−0.151	−0.151	−0.151	−0.151	−0.151							
REV	0.008	0.008	0.008	0.008	0.008	0.008						
MAX	0.290	0.290	0.290	0.290	0.290	0.290	0.290					
PRET	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001				
ILLIQ	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089			
BETA	0.439	0.439	0.439	0.439	0.439	0.439	0.439	0.439	0.439	0.439		
COSKEW	−0.127	−0.127	−0.127	−0.127	−0.127	−0.127	−0.127	−0.127	−0.127	−0.127	−0.127	
COKURT	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266

Note: This table presents the correlation between independent variables. The variables in the correlation matrix are industrial tail exposure risk (*ITER*), the natural log of market capitalization (*SIZE*), book-to-market ratio (*BM*), market leverage (*MLEV*), return on equity (*ROE*), illiquidity (*ILLIQ*), the average value of the five highest returns in the past month (*MAX*), stock returns for the previous month (*REV*), market beta (*BETA*), coskewness (*COSKEW*), cokurtosis (*COKURT*), and average past 12-month excess returns (*PAST RET*).

TABLE 3 Univariate portfolios of REITs sorted by ITER

Portfolio	Low	2	3	4	High	High–Low
ITER	−2.145	−0.911	−0.073	0.785	2.419	4.564
Excess Return	0.434	0.791	0.869	0.900	1.136	0.702***
	(1.108)	(2.312)	(2.718)	(2.632)	(2.785)	(2.974)
CAPM alpha	−0.070	0.323	0.361	0.400	0.556	0.626***
	(−0.227)	(1.186)	(1.459)	(1.436)	(1.755)	(2.634)
FF3 alpha	−0.096	0.293	0.335	0.367	0.522	0.618**
	(−0.388)	(1.390)	(1.675)	(1.693)	(1.966)	(2.554)
Carhart alpha	−0.063	0.388	0.423	0.487	0.727	0.790***
	(−0.251)	(1.878)	(2.216)	(2.306)	(2.968)	(3.613)

Note: This table presents the results of univariate portfolio sorts using ITER for the next 1-month average excess return. For every month, individual REITs are sorted into five quintile portfolios based on ITER. The Quintile 5 (1) portfolio includes REITs that have the highest (lowest) ITER during the previous month. The second-to-last column ("High–Low") reports the difference between Quintile 5 portfolio return and Quintile 1 portfolio return. The first row reports the average ITER of REITs in each ITER quintile, and the remaining rows show the average excess return and alpha (*CAPM alpha*, Fama-French three factors *(FF3) alpha*, and *Carhart alpha*) in each ITER quintile. Excess return is an equally weighted portfolio return in excess of the 1-month T-bill rate. *CAPM alpha* indicates the alpha from the capital asset pricing model of Sharpe (1964) based on the market factor. *Carhart alpha* denotes the alpha from the four-factor model of Carhart (1997) based on the market, size, book-to-market, and momentum factors. The *t*-statistics in the last column are calculated based on Newey and West's (1987) standard errors.

4 | EMPIRICAL RESULTS

In this section, we explore the intertemporal relationship between ITER and future returns. We conduct three main empirical asset pricing tests. First, univariate portfolio sort analysis is applied to investigate the distribution of future returns along with five quintile ITER portfolios. We also examine whether the return spread obtained by univariate portfolio sort is affected by other return factors using time-series regression tests. Second, we employ bivariate portfolio sort analysis to test for the predictability of ITER conditional on other firm-level risk factors. Finally, we conduct multivariate Fama–Macbeth (1973) cross-sectional regression tests to evaluate the risk premium of ITER after controlling for all other factors. For all of the empirical analyses, we use Newey and West's (1987) standard errors to mitigate the potential autocorrelation and heteroskedasticity.

4.1 | Univariate portfolio analysis

To test for the implication of ITER on expected future returns, we conduct the univariate portfolio analysis using the cross-section of ITER. The portfolio set of ITER starts with the sample from January 1993 to December 1995 and ends with the last sample from January 2018 to December 2020. For every month, individual REITs are sorted into five quintile portfolios by ITER. The Quintile 5 (1) portfolio includes REITs that have the highest (lowest) ITER during the previous month. For each portfolio, we estimate equally weighted 1-month-ahead excess returns over the 1-month T-bill rate. Table 3 reports the results of the univariate portfolio sort.

In the first row of Table 3, we report equally weighted ITER for five quintiles. We can identify a substantial variation of ITER in a range between −2.15 and 2.42. For 1-month-ahead portfolio returns, raw excess returns increase monotonically from 0.43% to 1.14% per month when the ITER portfolio moves from the lowest to the highest quintile. The average return spread between high (quintile 5) and low (quintile 1) is 0.70% per month (8.40% per annum) with a Newey–West (1987) t-statistic of 2.97, suggesting that REITs with higher ITER realize a significantly higher average return in the next month.

Since ITER can be correlated with several market risk factors, the results of raw returns might indirectly show the correlation between returns and firm-level systematic risk. To address this possibility, we further estimate the averaged monthly CAPM alpha, FF3 alpha, and Carhart alpha, which are obtained from Sharpe's (1965) CAPM model, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model, respectively.[8] The results in the last three columns of Table 3 show that all of the alphas have monotonically increasing trends when ITER increases from Quintiles 1 to 5. The difference in alpha between high and low portfolios is positive and statistically significant, with at least 0.62% per month (CAPM alpha). In particular, Carhart alpha registers the highest alpha spread of 0.79% per month with a Newey–West t-statistic of 3.60. These findings suggest that the positive return spread between high ITER REITs and low ITER REITs remains significant after controlling for different sets of well-known systematic return factors. In addition, we can identify that a positive relationship between returns and ITER is significantly driven by the outperformance of REITs with higher ITER, indicating that we can earn significantly positive returns by only taking a long position in REITs with higher ITER.

However, there could be more common factors that might affect the positive return spreads in Table 3. To investigate this possibility, we examine whether the return spread is consistent after controlling for different sets of risk factors, which are well known in the empirical asset pricing literature. To this end, we exploit the monthly excess return spread between high ITER REITs (Quintile 5) and low ITER REITs (Quintile 1) and conduct the following time-series regression.

$$r_t^{H-L} = \alpha + \gamma.X_t + \delta.RF_t + \varepsilon_t, \tag{13}$$

where r_t^{H-L} indicates the monthly difference in return between Quintiles 5 and 1 ITER portfolios, X_t is the vector of common factors, which contain Carhart's (1997) four-factor (*MKTRF*, *SMB*, *HML*, *MOM*), CFNAI, and change in housing price (Δ*House Price*), RF_t is additional risk factors, which are (1) profitability factor (*RMW*) and investment factor (*CMA*) from Fama and French's (2015) five-factor model, (2) Fama–French's short-term (*Short Rev*) and long-term reversal (*Long Rev*) factor, (3) Pastor and Stambaugh's (2003) liquidity factor, (4) Franzzini and Pedersen's (2014) betting-against-beta factor (*BAB*), and (5) Bali, Brown, Murray, and Tang's (2017) lottery demand factor (*FMAX*).[9] The coefficient of interest is α (intercept term), which shows the strength of return spread after controlling for different combinations of risk factors.

As shown in Table 4, all regression results provide positive and statistically significant alpha in a range between 0.84% and 1.31% per month with the minimum Newey–West t-statistic of 3.25. These results suggest that the future return spread based on ITER portfolios is not significantly driven by other risk factors, supporting the importance of ITER in explaining future returns.

[8] CAPM alpha is the alpha from the regression of the excess portfolio return on excess market return. FF3 alpha is the alpha obtained from the regression with three factors, excess market return, size, and book-to-market. Carhart alpha is the alpha relative to excess market return, size, book-to-market, and momentum.

[9] This indicator is frequently used to proxy for the overall economic activity (Allen et al., 2012; Bali et al., 2017). CFNAI is obtained from federal reserve bank of Chicago. Housing price is based on housing price index from Federal Housing Finance Agency. Profitability factor (*RMW*), investment factor (*CMA*), short-term (*Short Rev*), and long-term (*Long Rev*) reversal factors are obtained from Kenneth French's website. Liquidity factor is obtained from Pastor's website. Betting-against-beta factor (*BAB*) is obtained from Frazzini's data library. Finally, lotter demand factor (*FMAX*) is obtained from Bali's website.

TABLE 4 Alternative factor models

Dependent variable: Return difference between Quintiles 5 and 1 portfolios					
	(1)	(2)	(3)	(4)	(5)
CFNAI	−0.005***	−0.006***	−0.005***	−0.005***	−0.006***
	(−3.56)	(−3.91)	(−3.79)	(−3.42)	(−3.73)
ΔHouse Price	−1.057**	−0.945**	−1.045**	−0.785*	−1.018**
	(−2.15)	(−2.19)	(−2.23)	(−1.94)	(−2.21)
RMW	0.019				
	(0.18)				
CMA	−0.049				
	(−0.30)				
Short Rev		−0.208			
		(−1.38)			
Long Rev		0.323**			
		(2.32)			
Liquidity			v0.082*		
			(−1.76)		
BAB				−0.267**	
				(−2.10)	
FMAX					0.283*
					(1.85)
Constant	1.056***	1.093***	0.836***	1.164***	1.309***
	(3.26)	(3.87)	(3.25)	(3.62)	(3.36)
Carhart four-factors	Yes	Yes	Yes	Yes	Yes
R-squared	0.14	0.16	0.15	0.14	0.15
Observations	299	299	299	299	299

Note: This table presents the regression results of the "High (Quintile 5) minus Low (Quintile 1)" on five sets of risk factors. All regressions include Carhart's (1997) four factors (*MKTRF*, *SMB*, *HML*, *MOM*), Chicago Fed national activity index (*CFNAI*), and change in housing price (Δ*House Price*). The housing price is obtained from the federal housing finance agency. Column 1 includes the profitability factor (*RMW*) and investment factor (*CMA*) from the Fama and French's (2015) five-factor model. Column 2 contains the Fama–French short-term and long-term reversal factors. Columns 3–5 include the Pastor and Stambaugh's (2003) liquidity factor, Franzzini and Pedersen's (2014) betting-against-beta factor (*BAB*), and Bali et al.'s (2017) lottery demand factor (*FMAX*), respectively. The intercepts, which indicate alpha for respective models, are shown in the third last row. Newey–West (1987) standard error adjusted t-statistics are in parenthesis.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Interestingly, the coefficient of CFNAI is consistently negative and highly significant. This indicates that the ITER premium is higher during economic downturns. This finding is in line with Bali, Brown, and Tang (2017), who found higher uncertainty premiums during the recession period. In addition, the national housing price growth (Δ*House Price*) has negative effects on the return spread. This indicates that decreases in house prices make REIT investors more averse to tail risks, thereby reducing the return spread of ITER. This evidence is consistent with the theoretical mechanism of Lustig and Van Nieuwerburgh (2005) that a decrease in the ratio of housing wealth renders investors more risk-averse.

Our findings in this section suggest that REIT returns are highly priced by ITER and that ITER impacts are not affected by systematic market factors. Although there could be trading costs in the monthly rebalancing process, the high persistency of ITER from Figure 2 allows us to provide practical implications of the strongly positive returns from REITs with strong ITER.

4.2 | Bivariate portfolio analysis

To examine whether the higher excess returns of strong ITER REITs are explained by other firm-specific risk factors, we conduct a bivariate portfolio analysis. Specifically, we investigate whether the ITER equity premium remains after controlling for illiquidity, beta, coskewness, and cokurtosis. We first form low (less than 30%), medium (higher than 30% and less than 70%), and high (higher than 70%) groups sorted on illiquidity, beta, coskewness, and cokurtosis, respectively. Then, each group is further sorted into five quintile portfolios based on ITER. For each bivariate sorted portfolio, we compute equally weighted 1-month-ahead excess returns over the 1-month T-bill rate. Table 5 presents the results of bivariate sorts for four risk factors.

Panel A of Table 5 presents the excess returns sorted into illiquidity and ITER. Within each illiquidity group, we find that the fifth quintile ITER portfolio has consistently higher returns than the first quintile ITER. The return spreads between high and low quintile ITER portfolios are consistently positive and statistically significant for medium and high illiquidity groups. The average return spread is 0.81%, with a *t*-statistic of 3.81. In particular, high illiquidity REITs provide the highest return spread of 1.38% per month, suggesting that illiquid REITs are more priced by ITER than liquid REITs.

We further investigate whether the market beta (*BETA*) affects the return premiums of ITER. Panel B of Table 5 shows that all of the return differences are economically and statistically significant at least at a 5% level. The average return of high ITER REITs is 0.70% higher than that of low ITER REITs. This return difference is statistically significant at 1%. When comparing across three beta groups, the return spread does not show an outstanding difference, suggesting that the impact of ITER is not sensitive to the level of market beta.

As Harvey and Siddique (2000) find higher returns of lower coskewness (*COSKEW*) stocks, we test whether controlling for coskewness affects the impact of ITER. Panel C of Table 5 shows that the return differences are positive and statistically significant for all coskewness groups. The average value of return spread between the high and low ITER quintiles is highly positive at 0.71% (*t*-statistic = 3.11). Across the three coskewness groups, REITs in the low coskewness group show a relatively higher return premium of ITER than other REITs in the medium and high coskewness groups.

Finally, we examine the impact of cokurtosis (*COKURT*) documented by Dittmar (2002), who identifies that higher cokurtosis stocks have higher future expected returns. As shown in Panel D of Table 5, excess returns within each cokurtosis group follow a monotonic increasing trend when the ITER portfolio moves from the first quintile to the fifth quintile. The return differences between high and low ITER portfolios are economically large, at least 0.44%. REITs in the high ITER portfolio have an average excess return of 1.25%, while REITs in the low ITER portfolio show an average excess return of 0.43%. We further find that REITs in the low cokurtosis group are significantly more priced by ITER than REITs in other cokurtosis groups.

Next, we test whether the impact of ITER varies with firm characteristics. Specifically, we conduct bivariate portfolio analysis using size (*SIZE*), book-to-market ratio (*BM*), market leverage (*LEVERAGE*), and return on equity (*ROE*). Following Fama and French (1993), size is the logarithm of the market capitalization at the end of June at year t, and other financial variables are measured at the end of last fiscal year $t-1$ for the stock return from July of year t to June of year $t+$

TABLE 5 Risk characteristics and bivariate portfolio sort

Portfolio	Bivariate portfolio sorts Low	2	3	4	High	High–Low
Panel A. Illiquidity						
Low	0.776	0.773	1.034	0.773	1.146	0.370
	(2.29)	(2.46)	(3.19)	(2.26)	(2.75)	(1.49)
Medium	0.561	0.578	0.678	0.946	1.219	0.658**
	(1.49)	(1.60)	(2.08)	(2.39)	(2.77)	(2.06)
High	0.248	0.548	1.195	1.363	1.630	1.382***
	(0.52)	(1.21)	(3.12)	(3.01)	(3.12)	(3.67)
Average	0.517	0.626	0.924	1.018	1.325	0.808***
	(1.38)	(1.78)	(2.94)	(2.82)	(3.19)	(3.81)
Panel B. Beta						
Low	0.604	0.866	0.772	0.842	1.411	0.807***
	(1.64)	(2.38)	(2.67)	(2.79)	(3.54)	(2.65)
Medium	0.688	1.054	1.017	0.892	1.250	0.562***
	(1.84)	(3.04)	(3.27)	(2.61)	(3.92)	(2.62)
High	0.644	0.870	0.786	1.126	1.372	0.728**
	(1.20)	(1.62)	(1.86)	(2.61)	(2.45)	(2.12)
Average	0.646	0.941	0.872	0.945	1.348	0.702***
	(1.63)	(2.44)	(2.79)	(2.92)	(3.55)	(3.67)
Panel C. Coskewness						
Low	0.459	0.597	1.188	0.990	1.388	0.929***
	(1.02)	(1.41)	(2.98)	(2.68)	(2.94)	(2.94)
Medium	0.684	0.666	0.773	0.825	1.138	0.454*
	(1.67)	(2.03)	(2.36)	(2.73)	(2.51)	(1.71)
High	0.225	0.864	0.642	0.769	1.045	0.820***
	(0.58)	(2.39)	(1.67)	(2.03)	(2.30)	(2.64)
Average	0.481	0.707	0.852	0.855	1.191	0.710***
	(1.23)	(2.06)	(2.50)	(2.64)	(2.77)	(3.11)
Panel D. Cokurtosis						
Low	0.374	0.860	0.988	1.187	1.614	1.240***
	(0.80)	(1.95)	(2.69)	(2.54)	(2.91)	(3.30)
Medium	0.348	0.634	0.855	0.975	1.146	0.798***
	(0.86)	(1.88)	(2.45)	(2.90)	(2.82)	(2.91)
High	0.581	0.782	0.802	0.619	1.018	0.437*
	(1.48)	(2.31)	(2.17)	(1.69)	(2.39)	(1.73)
Average	0.432	0.748	0.876	0.942	1.249	0.817***
	(1.12)	(2.15)	(2.61)	(2.73)	(2.93)	(3.50)

Note: This table shows average out-of-sample monthly returns for the equally weighted portfolios constructed by double sorts, ITER and return patterns. The return patterns are illiquidity (*ILLIQ*), *BETA*, coskewness (*COSKEW*), and cokurtosis (*COKURT*). The three portfolios are first formed by illiquidity, beta, coskewness, and cokurtosis. Then, each portfolio is further sorted into five quintile portfolios based on ITER. The "High–Low" column indicates the return spread between the "high" ITER portfolio (quintile 5) and the "low" ITER portfolio (quintile 1). Newey-West (1987) standard error adjusted t-statistics are in parenthesis. The row "average" is the average 1-month excess return for the corresponding ITER quintile across five quintiles for beta, coskewness, cokurtosis, and illiquidity.

TABLE 6 Firm characteristics and ITER premiums

Characteristics	Portfolio	Low	High	High–Low
Size	Small	0.078	1.560	1.482***
		(0.17)	(3.10)	(3.94)
	Medium	0.571	1.249	0.678**
		(1.49)	(3.41)	(2.45)
	Large	0.684	1.129	0.445
		(2.07)	(2.39)	(1.58)
Book-to-market	Low	0.557	0.887	0.330
		(1.38)	(2.12)	(1.14)
	Medium	0.731	1.235	0.504**
		(2.29)	(3.13)	(1.82)
	High	0.279	1.535	1.256***
		(0.49)	(2.80)	(2.92)
Leverage	Low	0.655	0.984	0.329
		(2.11)	(3.25)	(1.41)
	Medium	0.656	1.316	0.660*
		(1.76)	(3.06)	(1.83)
	High	0.435	1.353	0.918**
		(0.71)	(2.18)	(2.49)
Return on equity	Low	0.359	1.455	1.096***
		(0.70)	(2.81)	(2.71)
	Medium	0.786	1.289	0.503**
		(2.05)	(3.70)	(2.55)
	High	0.616	0.953	0.337
		(1.72)	(2.07)	(1.04)

Note: This table presents average out-of-sample monthly returns for the equally weighted portfolios constructed by double sorts, ITER, and firm characteristics. The REITs' characteristics are the log of market capitalization (*Size*), book-to-market ratio (*BM*), market leverage (*MLEV*), and return on equity (*ROE*). The three portfolios are first formed by *Size*, *BM*, *MLEV*, and *ROE*. Then, each portfolio is further sorted into five quintile portfolios based on ITER. The "High–Low" column indicates the return spread between the "high" ITER portfolio (Quintile 5) and the "low" ITER portfolio (Quintile 1). Newey–West (1987) standard error adjusted *t*-statistics are in parenthesis. The row "average" is the average 1-month excess return or 12-month excess return for the corresponding ITER quintile across three quintiles for *SIZE*, *BM*, *MLEV*, and *ROE*.

1. This estimation allows the stock returns to have enough time to reflect firm characteristics. The double sort portfolio takes the same steps as in the previous approach. We first form low (less than 30%), medium (higher than 30% and less than 70%), and high (higher than 70%) groups sorted by size, book-to-market, leverage, and return on equity. Within each group, we then form five quintile portfolios based on ITER. For each bivariate sorted portfolio, we compute equally weighted 1-month-ahead excess returns over the 1-month T-bill rate. Table 6 reports expected excess returns of bivariate portfolios for low, high, and high minus low on four firm characteristics.

First, size and book-to-market ratio have been the two most important asset pricing factors (Fama & French, 1992). We investigate whether these factors affect the positive impact of ITER on future excess returns. For firm size, we find that REITs with higher ITER have higher future excess returns than REITs with low ITER for all of the size groups. In particular, REITs in small-size groups show the largest return difference of 1.48% (17.76% per annum). This suggests that small-size REITs are priced by ITER more substantially than other size groups. When controlling for the book-to-market ratio (*BM*), the return differences between the highest and lowest ITER group are all positive and statistically significant for medium and large BM groups. The magnitude of return difference increases when portfolios move from the low BM group to the high BM group. This indicates that value firms are more sensitively priced by ITER.

Second, leverage is an important factor of stock returns in the sense that excess use of leverage could be associated with enhanced financial risk due to deterioration of financial flexibility (Gu et al., 2018; Hahn & Lee, 2009). Thus, we further conduct double-sorted portfolio analysis with market leverage (*MLEV*). The results show that the positive relation between ITER and future excess return holds for three leverage groups. However, the return difference in the low leverage group is not statistically significant. In addition, the size of the return difference increases with the level of leverage. Within the high leverage group, the return difference is 0.92%, which is over two times larger than the return difference within the low leverage group. This finding suggests that firms with less debt capacity are more expected to have higher risk premiums, in line with Hahn and Lee (2009).

Finally, Novy-Marx (2013) documents that profitable firms provide significantly higher future excess returns than unprofitable firms. To test the impact of profitability on our results, we exploit return on equity (*ROE*) as a proxy for the profitability of REIT. The results show that the positive impact of ITER is applied to the three *ROE* groups. However, the return difference in the high *ROE* group is not statistically significant. On the other hand, REITs in the low ROE group have a significantly higher return spread than REITs in other *ROE* groups. This suggests that REITs with poorer performance of profitabilityshow higher ITER premiums than REITs with better profitability.

To summarize the findings in this section, we document that the return premiums of ITER are not obviously explained by other factors. Throughout all return and firm characteristics, ITER consistently predicts positive future excess returns, suggesting that the cross-sectional characteristics of REITs cannot completely disentangle the return premium of ITER. However, we identify that the economic magnitudes of the ITER premium vary with other firm factors, implying that several firm-specific variables may influence the results in a multivariate way. Since our results are based on bivariate sorts with only one control variable, it is a natural question to address whether ITER impacts are robust when controlling for multivariate variables simultaneously. We address this question by applying Fama–MacBeth's (1973) cross-sectional multivariate regression in the next section.

4.3 | Multivariate analysis

As previous portfolio analysis is based on the nonparametric way, we can find the nonlinear impact of ITER on future returns. However, portfolio analysis cannot include multiple control variables in a single empirical test. Thus, we exploit multivariate analysis to examine the impact of ITER on future expected returns after controlling for various explanatory variables. Specifically, we conduct Fama and MacBeth's (1973) cross-sectional regressions with various explanatory variables using the sample period of December 1993 to December 2020. The specification of the monthly cross-sectional regression for the first four columns is as follows:

$$r_{i,t+1} = \alpha_t + \beta_{1,t}.ITER_{i,t} + \beta_{2,t}.X_{i,t} + \varepsilon_{i,t+1}, \tag{14}$$

where $r_{i,t+1}$ is the excess return (%) of REIT i in month $t + 1$, $ITER_{i,t}$ is the ITER of REIT i in month t, and $X_{i,t}$ is a combination of control variables (*Size*, book-to-market ratio (*BM*), market leverage (*MLEV*), return on equity *(ROE*), short-term reversal (*REV*), demand for lottery stocks (*MAX*), past return (*PAST RET*), illiquidity (*ILLIQ*), market beta (*BETA*), coskewness (*COSKEW*), and cokurtosis (*COKURT*)). All of the control variables are observable up to month t for REIT i. For each month from December 1995 to December 2020, the cross-sectional return is conducted. Table 7 reports the time-series averaged coefficients of the monthly cross-sectional regression.

In Column 1, we test for the impact of ITER on 1-month-ahead excess return without controlling for other control variables. The result shows that ITER has a strong positive impact on the next month's excess return with a coefficient estimate of 0.148 (Newey–West (1987) t-statistic is 3.16). To evaluate the economic significance of this average coefficient estimate, we exploit the difference in average ITER ($4.56 = 2.42 - (-2.15)$) between the fifth quintile and first quintile portfolios from the univariate portfolios in Table 4. This difference generates, on average, 0.68% ($= 0.148 \times 4.57$) per month (8.12% per annum). Thus, we can expect economically significant increases in future stock returns if REITs move from the first quintile to the fifth quintile portfolio group.

In Column 2, we include firm characteristics (*SIZE*, *BM*, *MLEV*, and *ROE*). The regression result shows that the book-to-market ratio has a highly significant and positive impact on future returns. The coefficient estimate of return on equity is positive and statistically significant at 10%. The coefficient estimate of ITER is 0.115 with a t-statistic of 2.97, indicating that the positive impact of ITER on returns remains significant after controlling for firm characteristics. In Column 3, we add three well-known return factors, which are Jegadeesh's (1990) short-term reversal (*REV*), Bali et al. (2011) demand for lottery stocks (*MAX*), and past return (*PAST RET*). The result shows that the coefficient estimate of ITER is highly significant, with a t-statistic of 3.41. Among additional factors, short-term reversal (*REV*) has a strongly negative and statistically significant effect, in line with Jegadeesh (1990).

Finally, we add return patterns (*ILLIQ*, *BETA*, *COSKEW*, *COKURT*) as control variables in the regression. Column 4 shows that the coefficient estimate of ITER is highly positive and statistically significant at the 1% level. The Newey–West t-statistic is 3.91, which exceeds the level of 3.0 in Harvey et al. (2016). Moving from the ITER first quintile to the ITER fifth quintile provides, on average, 0.65% ($= 0.143 \times 4.56$) per month. The results for other explanatory variables show that the value effect (*BM*) and profitability effect (*ROE*) are positive and statistically significant, while the size and leverage effects are relatively weaker. Among return characteristics, short-term reversal (*REV*) shows a highly negative coefficient estimate, indicating that monthly return reversal effects are strong in the REIT market.

To assess the predictive power of ITER, we further investigate whether the positive impact of ITER on future excess returns holds over one month. Table 8 reports the results from cross-sectional regressions with control variables (Panel A) and without control variables (Panel B). We exploit the control variables used in Column 4 of Table 7. As shown from both panels of Table 8, the explanatory power of ITER is consistently effective on at least 12-month-ahead returns. This suggests that REIT investors persistently require higher return premiums from REITs with higher ITER. This evidence is also in line with the findings from the ITER transition matrix of Figure 2 in that REITs with higher ITER generally show higher ITER in the future as well.

TABLE 7 Multivariate cross-sectional regression

Dependent variable: $r_{i,t+1}$				
	(1)	**(2)**	**(3)**	**(4)**
ITER	0.148***	0.115***	0.129***	0.143***
	(3.16)	(2.97)	(3.41)	(3.91)
SIZE		−0.021	−0.024	0.032
		(−0.36)	(−0.42)	(0.54)
BM		0.469**	0.455**	0.523***
		(2.16)	(2.42)	(3.13)
MLEV		−0.691	−0.737	−0.438
		(−1.21)	(−1.33)	(−0.84)
ROE		2.689*	2.680*	3.104**
		(1.72)	(1.79)	(2.06)
REV			−0.067***	−0.059***
			(−4.01)	(−3.26)
MAX			−0.059	−0.043
			(−0.41)	(−0.26)
PAST RET			0.044*	0.040*
			(1.88)	(1.80)
ILLIQ				0.869
				(1.54)
BETA				−0.658
				(−1.05)
COSKEW				−0.867
				(−1.16)
COKURT				0.470*
				(1.78)
Constant	0.806**	0.873*	1.113**	0.073
	(2.50)	(1.71)	(2.07)	(0.12)
R-squared	0.025	0.156	0.242	0.336
Obs.	28,191	28,191	28,191	28,191

Note: This table presents the Fama–Macbeth (1973) regression results of 1-month-ahead excess returns on ITER and other explanatory variables. Explanatory variables are the natural log of market capitalization (*SIZE*), book-to-market ratio (*BM*), market leverage (*MLEV*), return on equity (*ROE*), short-term reversal (*REV*), average five highest return in the past month (*MAX*), past 12-month average excess return (*PAST RET*), Amihud's illiquidity (*ILLIQ*), market beta (*BETA*), coskewness (*COSKEW*), and cokurtosis (*COKURT*). The size is measured at the end of June of year t for stock returns from July of year t to June of year $t+1$. The other firm characteristics (*BM*, *MLEV*, and *ROE*) are estimated at the end of the last fiscal year $t-1$ for stock returns from July of year t to June of year $t+1$. The return characteristics (*BETA*, *COSKEW*, and *COKURT*) are measured using a 1-year daily return up to month t. All of the independent variables are winsorized at the 1% and 99% levels. The sample period for the regression is from December 1995 to December 2020. Newey–West (1987) standard error adjusted t-statistics are in parenthesis.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 8 The predictive power of ITER

	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$t+7$	$t+8$	$t+9$	$t+10$	$t+11$	$t+12$
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Panel A. Predictive regression without control variables											
ITER	0.135***	0.127***	0.156***	0.180***	0.177***	0.155***	0.154***	0.115**	0.129**	0.123**	0.111*
	(3.06)	(2.77)	(3.48)	(3.68)	(3.83)	(3.20)	(3.04)	(2.19)	(2.54)	(2.25)	(1.89)
Control	No	No	No	No	No	No	No	No	No	No	No
R-squared	0.025	0.025	0.024	0.024	0.023	0.024	0.024	0.024	0.024	0.025	0.026
Panel B. Predictive regression with control variables											
ITER	0.109***	0.085**	0.116***	0.135***	0.144***	0.153***	0.139***	0.120***	0.149***	0.091**	0.122**
	(3.03)	(2.27)	(3.12)	(3.31)	(3.35)	(3.57)	(3.03)	(3.01)	(3.39)	(1.98)	(2.55)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.327	0.327	0.322	0.321	0.321	0.315	0.315	0.323	0.312	0.316	0.318

Note: This table presents the Fama–Macbeth (1973) regression results of future returns on ITER with or without control variables. From Columns 1 to 11, monthly excess returns 2- to 12-months ahead are dependent variables. Panels A and B show the results based on regressions without control variables and with control variables, respectively. Control variables contain all variables used in Table 8 (*SIZE*, *BM*, *MLEV*, *ROE*, *REV*, *MAX*, *PAST RET*, *ILLIQ*, *BETA*, *COSKEW*, and *COKURT*). All of the independent variables are winsorized at the 1% and 99% levels. The sample period for the regression is from December 1995 to December 2020. Newey–West (1987) standard error adjusted *t*-statistics are in parenthesis.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

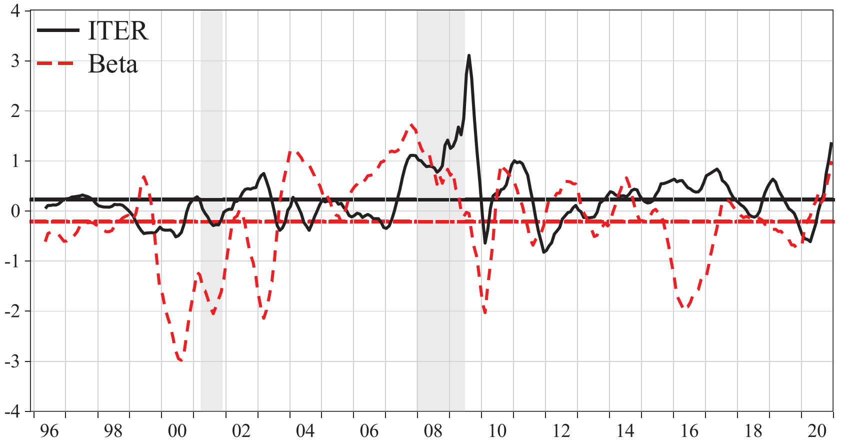

FIGURE 3 Time-varying ITER and *BETA* coefficients [Color figure can be viewed at wileyonlinelibrary.com]

Note: This figure presents the 6-month moving average of the monthly slope coefficients of ITER and *BETA*. To facilitate the comparison, both variables are standardized to have zero mean and one standard deviation. In this figure, *BETA* is obtained from a 36-month rolling window as in the estimation of ITER. The monthly slope coefficients of ITER and beta are obtained from the monthly Fama–Macbeth (1973) cross-sectional regression

4.4 | Time variations of ITER premium

The results have thus far shown that REITs with higher ITER have significantly stronger returns than REITs with lower ITER. The return premium of ITER is based on the average value of estimates from 1995 to 2020. However, it is well demonstrated that risk aversion is time-varying (e.g., see Barberis et al., 2001). Guiso et al. (2018) and Campbell & Cochrane (1999) empirically document that proxies for risk aversion increase substantially after the subprime mortgage crisis. Furthermore, Chen et al. (2012) theorize that the risk premium of extreme downside events increases substantially after a disaster because the heterogeneous beliefs about disasters decrease. Thus, it is natural to raise a question about whether the impact of ITER varies with different market states in which investors may have different levels of risk aversion. In addition, it is also important to investigate whether our tail risk coefficient captures different patterns of dynamic risk aversion from the coefficients of beta, which is based on the linear dependence between REIT and market returns.

To answer this question, we plot the monthly slope coefficients of ITER and market beta over the sample period. Figure 3 shows the 6-month moving averages of the slope coefficients of ITER and beta. To compare the economic impacts, we standardize two independent variables (*ITER* and *BETA*) to have zero mean and one standard deviation. We further draw the average value of monthly coefficients for both variables. In line with the theoretical prediction, we find that the slope coefficient of ITER shows a countercyclical movement against the aggregate economic activity. This finding is also consistent with the negative impact of CFNAI on the return spread of ITER in Table 4. Specifically, the slope coefficient increases substantially during the 2008 subprime mortgage crisis. After the recession period, the slope coefficient shows stable behavior around their mean. More recently, the slope coefficients show another spike in response to the Coronavirus (COVID-19) crash. These findings indicate that the return premium of ITER is highly dependent on the state of the economy and the time-varying risk aversion of investors.

When it comes to monthly coefficients of the market beta, we find that overall movements during volatile periods show similar patterns with ITER. However, the ITER coefficient captures a more significant impact during the subprime mortgage crisis. In addition, the coefficients of the market beta show substantially negative impacts during relatively stable periods. This suggests that ITER captures time-varying risk premiums that are significantly different from the classical systematic risk. In particular, ITER has much stronger explanatory powers over the market beta during extremely volatile periods.

To further check the impacts of ITER in different market states, we conduct cross-sectional regression for NBER crisis periods (2003M03–2003M11; 2007M12–2009M06) and non-NBER crisis periods. The results from Table 9 show that the impact of ITER is economically large during economic recession periods. The coefficient estimate of ITER during the NBER crisis periods is over four times greater than the rest of the periods. These results confirm that the ITER premium is alive across all periods but much stronger when the market is extremely in turmoil.

4.5 | Robustness check

In this section, we examine whether the return premium of ITER is robust to different estimation procedures. We first examine whether our results are affected by different industrial classifications (5, 17, 30, and 48 Fama–French industries), cutoffs (10% and 20%), and estimation window sizes (24 and 60 months). In addition, we test for the robustness of the results after excluding the 10th decile of ITER to investigate whether our results are driven by the highest ITER group. For each specification, we conduct a univariate portfolio analysis and Fama–MacBeth's (1973) cross-sectional regression with full control variables. Table 10 reports the high minus low return spreads from univariate portfolio analysis and coefficients of ITER from the cross-sectional regression. For different industrial classifications, cutoffs, and window horizons, we find that the impact of ITER remains positive and statistically significant at least at a 5% level. When we exclude the highest decile of ITER, the slope coefficient of ITER is still positive and significant at the 5% level. This suggests that our results are not solely driven by the strongest ITER REITs.

5 | UNDERSTANDING THE EFFECTS OF ITER

The results have thus far shown that ITER is strongly and positively associated with future returns in the cross-section of REITs. This predictive effect is robust to known firm characteristics that have explained stock returns in the existing studies. However, there could be other explanations for this persistent impact of ITER. This section aims to provide a battery of tests to explore various mechanisms for the effects of ITER.

5.1 | Cross-sectional effects of industries

Although ITER reflects the variation of BTER of 12 industries, each estimated BTER might have a different level of effects on the cross-sectional predictability across rolling windows. For example, some industries with higher BTER could drive the ITER premium. More importantly, the overall evolution of ITER might be associated with major industries that are large in terms of

TABLE 9 Financial crisis and ITER premium

Dependent variable: $r_{i,t+1}$	Financial crisis	Nonfinancial crisis
ITER	0.462***	0.108***
	(2.79)	(3.24)
SIZE	−0.135	0.042
	(−0.68)	(0.70)
BM	1.350*	0.472***
	(1.79)	(2.90)
MLEV	−4.397	−0.036
	(−1.38)	(−0.09)
ROE	1.550	3.021*
	(0.32)	(1.91)
REV	−0.050	−0.058***
	(−0.86)	(−3.12)
MAX	0.146	−0.048
	(0.52)	(−0.27)
PAST RET	0.291***	0.028
	(3.83)	(1.28)
ILLIQ	−0.419	0.966
	(−1.26)	(1.61)
BETA	−5.113	−0.435
	(−1.56)	(−0.75)
COSKEW	−1.882	−0.778
	(−0.39)	(−1.25)
COKURT	2.213	0.360*
	(1.20)	(1.73)
Constant	1.847	−0.126
	(0.83)	(−0.20)
R-squared	0.321	0.336
Obs.	2550	25,641

Note: This table presents the Fama–Macbeth (1973) regression results based on subsample of recession period and nonrecession period. We use the US recession period defined by NBER (200303–200311) and (200712–200906) in our sample period. We include the full control variables used in Column 5 of Table 8. All of the independent variables are winsorized at the 1% and 99% levels. Newey–West (1987) standard error adjusted *t*-statistics are in parenthesis.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

market capitalization and thus fundamentally more associated with REITs. Thus, we investigate how cross-sectional characteristics of industries comprise the ITER effect.

First, we examine how the tail risk premium varies with the level of BTER over the sample period. Methodologically, the positive relationship between ITER and stock returns could be more strongly explained by particular industries having stronger BTER than other industries. This is because ITER is constructed based on PCA, which provides more weights on variables with higher variation within the estimation period. However, this might not be the case, especially during extremely volatile periods when most industries are exposed to aggregate adverse shocks. For

TABLE 10 Robustness check

	Univariate portfolio High–Low	Fama–Macbeth (1973) Coefficients
Fama–French 5 industry	0.733***	0.179***
	(3.47)	(3.53)
Fama–French 17 industry	0.751***	0.106***
	(3.73)	(3.72)
Fama–French 30 industry	0.774***	0.086***
	(3.83)	(3.85)
Fama–French 48 industry	0.767***	0.073***
	(3.84)	(3.69)
10% cutoff	0.807***	0.122***
	(4.24)	(3.70)
20% cutoff	0.483**	0.134***
	(2.07)	(4.09)
24-month	0.507***	0.152***
	(2.308)	(3.74)
60-month	0.746***	0.109***
	(3.40)	(3.20)
Exclude 10th quintile of ITER	0.512***	0.105**
	(2.63)	(2.36)

Note: This table presents slope coefficients of different ITER measures from Fama–Macbeth (1973) regressions of 1-month-ahead excess returns on ITER and full control variables as in the last column of Table 8. The coefficients of Fama–French 5, 17, 30, 48 industry are obtained by using the same method of estimating ITER but applying different industrial classifications. The 10% and 20% cutoffs indicate the threshold for the estimation of tail dependence. The coefficients of 1 and 5 years are based on ITERs from 24- and 60-month lengths, respectively. In the last row, we test the impact of ITER after excluding the 10th quintile of ITER. Newey–West (1987) standard error adjusted *t*-statistics are in parenthesis.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

example, the highest BTER of a manufacturing industry may not drive the ITER effects during crisis periods when investors have to consider all industries associated with their exposures rather than a particular industry due to highly increased systematic risk (Barro, 2006; Kelly & Jiang, 2014).

To explore the varying effects of BTER, we conduct Fama–Macbeth's (1973) regression tests with full control variables by replacing ITER with BTER registered in minimum, Quartiles 1 to 4, and maximum among 12 Fama–French industries for each rolling window.[10] Panel A of Table 11 provides the coefficient estimates of varying BTERs for the full sample and crisis period. The results of the full sample in Column 1 show that the positive impacts of BTER on stock returns increase with the level of BTER. This suggests that industries with stronger BTER are major sources of the ITER effects, consistent with how ITER is constructed based on PCA. In other words, the tail risk premium could be associated with certain industries that have shown higher tail dependence over the past few years. However, this implication might not be applicable during extremely volatile periods. Column 2 of Panel A shows that the effects of higher BTER do not

[10] For each quartile, we use the average value of three BTER within that quartile.

TABLE 11 Cross-sectional effects of industries

Panel A. Varying effects of bivariate tail exposure risk (BTER)		
Dependent variable: $r_{i,t+1}$		
BTER among 12 industries	Full-sample (1)	Crisis period (2)
Minimum	0.035	0.559**
	(0.58)	(2.73)
Quartile 1	0.069	0.833***
	(0.94)	(3.01)
Quartile 2	0.207***	0.929***
	(2.87)	(3.48)
Quartile 3	0.245***	0.519
	(3.26)	(1.62)
Quartile 4	0.260***	0.245
	(2.98)	(0.61)
Maximum	0.281***	0.565
	(3.38)	(1.52)
Panel B. Impacts of major industries		
Dependent variable: $r_{i,t+1}$	Top three Industries (1)	Top six Industries (2)
ITER × Major Industry BTER	0.077*	0.096**
	(1.90)	(2.02)
ITER	0.171***	0.168***
	(4.06)	(3.96)
Control	Yes	Yes
R-squared	0.373	0.376
Obs.	28,191	28,191

Note: This table presents the varying effects of industries based on the BTER measure using Fama–MacBeth (1973) regression tests with full control variables. Panel A reports the estimated coefficients of BTER at minimum, Quartiles 1 to 4, and maximum among 12 BTERs for each rolling window. We use the mean BTER for three industries within each quartile. The crisis period indicates the recession period defined by NBER (200303–200311) and (200712–200906) over the sample period. Panel B provides the regression coefficients of ITER and the interaction between ITER and the mean BTER of major industries. Major industry is defined based on the rank of market capitalization across 12 Fama–French industries over the sample period. The top three and six industries indicate industries ranked within the top three and six, respectively, among the 12 industries.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

show greater effects compared to those of lower BTER. Although overall coefficient estimates are largely increased, only BTER within less than Quartile 3 shows statistically significant effects with greater degrees. In addition, the coefficient size is not linearly distributed, as shown in the full-sample test. Given that sectoral stock returns are directly subject to the fluctuation of the broad US stock market, this finding suggests that various industries should be considered to well reflect the comprehensive tail dependence structure of REITs with multiple sectors and that our PCA approach provides balanced results in the sense that it places larger weights on extreme BTER but does not ignore a low level of BTER in the estimation.

Another question that naturally arises is which industries are more associated with the effects of ITER. The recent literature documents that certain sectors drive macroeconomic risks (e.g., Atalay et al., 2018; Segal., 2019). In addition, systematic tail risk can be driven by major industries with large market power rather than peripheral industries, which have less economic impact (Acemoglu et al., 2017). Thus, we can expect that investors would require larger return premiums from REITs that have higher tail dependence on dominant sectors because these REITs are more vulnerable to the aggregate extreme risk. To investigate the differential effects of major industries, we construct the mean BTER of major industries defined as the top three and six based on market capitalization across 12 Fama–French industries over the sample period. We use these variables in an interaction term with ITER using the full control variables within the Fama–MacBeth (1973) regression. The variables of the mean BTER of major industries are standardized to have a mean of zero and a standard deviation of 1 to help interpret the results.

Panel B of Table 11 reports the coefficient estimates of interaction terms between the ITER and the mean BTER of major industries. Consistent with our expectation, the coefficient on the interaction term is positive and statistically significant for both the top three and top six industries. For the economic magnitude, a 1-standard-deviation increase in the mean BTER of major industries leads to at least a 45.02% increase in the ITER effect compared to the average state of major industries. This finding implies that REITs with higher negative extreme dependence on dominant industries are required to provide higher returns.

5.2 | ITER and local market

As our ITER measure is only based on the distribution of stock returns, it may not reflect underlying mechanisms that drive the positive return premium of REITs. Although we investigate the heterogeneous effects using standard asset pricing characteristics in bivariate portfolio analysis, REITs have significantly different asset structures from nonfinancial firms, especially with regard to property holdings. Thus, the impacts of the local market where properties operate should be important channels for the cross-section of REITs returns (e.g., Adams et al., 2015; Ling et al., 2021, 2022).

This section explores the local market channels by focusing on the tail risk of local industries and the geographical concentration of REITs in terms of operating properties. First, it is natural to raise a question about how our ITER measure is related to the tail risk of the local market since local industries are closely associated with local real estate (Tuzel & Zhang, 2017). In addition, Smajlbegovic (2019) documents that regional economic activity is positively and significantly related to the cross-section of returns. This suggests that increases in the tail risk of local industries could be positively associated with the effects of ITER. Another dimension of the local market from the firm-level perspective is how geographical concentration or dispersion is associated with asset pricing anomalies. Previous studies have shown that geographically more concentrated firms or institutions tend to have a diversification discount in their asset price (e.g., Garcia & Norli, 2012; Ling et al., 2020). In this sense, we can expect that REITs with higher geographical concentration could have higher return premiums of ITER since these REITs may not sufficiently diversify industrial tail risk.

To explore how two geographical components affect the effects of ITER, we measure REITs' portfolio weight for each US State using property-level information from the S&P Global Real Estate Properties database (formerly SNL Real Estate Database). Following Ling et al. (2021), we estimate portfolio weight based on SNL's adjusted cost, which is defined as the maximum of the book value, the initial cost, and the historic cost of the property before deducting capital expenditures and tax depreciation. For REIT i, the property weight of state s is calculated as follows:

$$property\ weight_{i,s,y} = \frac{\sum_{j=1}^{N_{s,y}} adj\_cost_{i,s,y}}{\sum_{s=1}^{N_s}\left(\sum_{j=1}^{N_{s,y}} adj\_cost_{i,s,y}\right)}, \tag{15}$$

where $adj\_cost_{i,s,y}$ is the adjusted cost of property j of REIT i in state s at the beginning of year y, $N_{s,y}$ is the number of properties in state s, and $N_{s,y}$ is the number of states where properties of REIT i appear. This measure indicates the relative proportion of property investments across US States. Similar to Smajlbegovic (2019) and Song and Zhang (2022), we employ local weights to obtain the firm-level exposure to the tail risk of local industries:

$$Local\ Tail\ Risk_{i,t} = \sum_{s=1}^{N_s}\left[property\ weight_{i,s,t} \times \left(\sum_{k=1}^{N_k} w_{k,s,t} \times TR_{k,s,t}\right)\right], \tag{16}$$

Where $TR_{k,t}$ is the tail risk of industry k in state s at month t, estimated as the ES over the last 36 months based on daily residual returns relative to Carhart's (1997) four factors. $w_{k,t}$ is the weight of industry k based on market capitalization at the end of the last month. Finally, we use the Herfindahl–Hirschman concentration to estimate the geographical concentration of REIT i:

$$Local\ HHI_{i,t} = \sum_{s=1}^{N_s}\left(property\ weight_{i,s,t}^2\right). \tag{17}$$

Based on two estimated local measures, we investigate how REITs' local factors affect the effects of ITER. First, we run a cross-sectional regression to examine how ITER is affected by two variables. In Column 1 of Panel A of Table 12, we can identify that the ITER measure is highly and positively associated with local tail risk and local Herfindahl-Hirschman index (HHI), suggesting that the variation of ITER reflects the local characteristics of REITs. This naturally incurs a question about how much these regional factors of REITs account for the premium of REITs. To answer this question, we obtain residual ITER ($ITER^{\perp}$) orthogonalized to the local tail risk and local HHI variables and use it to run the Fama–MacBeth (1973) regression test. Column 2 of Panel A shows that the estimated coefficient is decreased but still highly positive and statistically significant at the 1% level. In terms of economic magnitude, excluding two variables from the ITER measure reduces the coefficient estimate by 24.48%, compared to the coefficient of ITER in Column 4 of Table 7. This implies that ITER captures asset pricing anomalies not fully explained by local traits of REITs.

We further investigate how return spreads of ITER are affected by local factors. To this end, we use raw excess returns and the Carhart alpha to conduct a bivariate sort similar to Table 6. Panel B of Table 12 reports "high minus low" return spreads of ITER across low, medium, and high groups of local tail risk and local HHI, respectively.[11] The last column presents the average return spreads across the three groups. As predicted, the results show that the ITER return spreads of both raw excess returns and Carhart alpha increase with the level of local tail risk and local HHI. The return spreads of the high group for both local variables indicate at least 12.82% per annum.

[11] For the bivariate sort of local HHI, REITs operating in only one region (*Local HHI* = 1) are excluded to avoid our results being driven by extremely concentrated REITs. Including these REITs provide qualitatively similar results.

TABLE 12 Local market implications

Panel A. Impacts of local industries					
		ITER		$r_{i,t+1}$	
Dependent variable:		**(1)**		**(2)**	
Local Tail Risk		0.037***			
		(2.83)			
Local HHI		0.026**			
		(2.54)			
$ITER^{\perp}$				0.108***	
				(3.08)	
Control		Yes		Yes	
R-squared		0.378		0.370	
Obs.		22,662		22,660	
Panel B. Bivariate sort					
		Low	**Medium**	**High**	**Average**
Local Tail Risk	Raw excess return	0.473	0.850**	1.068***	0.818***
		(1.368)	(2.573)	(3.121)	(3.038)
	Carhart alpha	0.478	0.831**	1.197***	0.852***
		(1.375)	(2.570)	(3.491)	(3.197)
Local HHI	Raw excess return	0.587	0.923**	1.172**	0.822***
		(1.635)	(2.508)	(1.991)	(2.728)
	Carhart alpha	0.588	0.862**	1.201**	0.796***
		(1.610)	(2.437)	(1.999)	(2.701)

Note: This table presents the results associated with the effects of local characteristics of REITs. Column 1 of Panel A shows the coefficient estimates of local tail risk and local HHI by conducting the cross-sectional regression of ITER on these two variables and other control variables. Column 2 of Panel A presents the coefficient estimate of ITER orthogonalized against the local tail risk and local HHI. Panel B reports the high minus low spreads of raw returns and Carhart alpha sorted by ITER and each local characteristic. The portfolio is first formed into three portfolios by local characteristics. Consistent with previous bivariate sorting, we used low (less than 30%), medium (higher than 30% and less than 70%), and high (higher than 70%) groups. Then, each formed portfolio is further sorted into five quintile portfolios based on ITER. The reported value indicates the return spread of high minus low ITER within each group of local characteristics.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

These results suggest that the local market characteristics of REITs are an important channel of tail risk premiums in the REIT market.

5.3 | ITER and home-biased investors

Finally, we explore the implications of home-biased investors in our results. It has been well-established that investors tend to show home-biased investment in firms near their location (e.g., Baik et al., 2010; Coval & Moskowitz, 1999, 2001). Previous studies show that home-biased investors achieve better performance by taking advantage of information through local channels (e.g., Cohen et al., 2008; Miller, 2006). Importantly, asset prices of firms with higher ownership of home-biased investors have shown different patterns (Bernile et al., 2015). Thus, as an extension of the local implication in Section 5.2., we further investigate the impacts of home-based investors on the ITER effects. Following Coval and Moskowitz (2001), we construct quarterly fund-level home-biased measures using the mutual fund holding data from the CRSP Survivor-Bias-Free US Mutual Fund Database and Thomson Reuters S12 Mutual Fund Holdings Database. Based on the standard approach (e.g., Cremers et al., 2016; Kacperczyk et al., 2005), we focus on actively managed equity mutual funds that have over \$5 million of total investment and over 10 invested stocks. Then, we measure the level of home bias for each fund using the locational information of fund management companies and invested stocks.[12] Specifically, we estimate the following measure:

$$Home\ Biased_{f,q} = \sum_{j=1}^{N_{f,q}} \left(w_{j,q}^{invested} - w_{j,q}^{benchmark} \right)_{distance_{f \leftrightarrow j} < D}, \tag{18}$$

where $distance_{f \leftrightarrow j} < D$ denotes the condition that the distance between fund f and stock j at year y *is* less than D, which is the threshold of proximity. For the distance, we compute the great circle distance between the zip code of the fund management company of fund f and the zip code of firm i using the corresponding latitude and longitude information. $w_{j,q}^{invested}$ is the investment weight of fund i on stock j in quarter q, and $w_{j,q}^{benchmark}$ is the market capitalization weight of stock j in the portfolio of fund i in quarter q. $N_{f,q}$ is the number of stocks invested by fund f. Finally, $Home\ Biased_{f,q}$ indicates how much investment of fund f is biased within the distance D. To explore varying effects of the distance threshold, we use not only 100 km, which is employed by Coval and Moskowitz (2001) but also 500 and 1000 km. We then calculate REIT i's home-biased exposure as follows:

$$Home\ Biased\ Exposure_{i,t} = \sum_{f=1}^{N_{i,q}} (w_{f,q} \times Home\ Biased_{f,q}), \tag{19}$$

where $w_{f,q}$ is the ownership weight of fund f at quarter q and $N_{i,q}$ is the number of funds that invest in REIT i. $Home\ Biased\ Exposure_{i,t}$ indicates how much REIT i is exposed to home-based investors in terms of their stock ownership. If there is locational information asymmetry and home-biased investors are better informed, we can predict that REITs with higher ownership of home-based funds show greater ITER effects.

Based on the estimated home-biased exposure measure, we divide REITs into low, medium, and high groups for each month and conduct Fama–MacBeth's (1973) cross-sectional regression tests with full control variables. Table 13 reports the estimated coefficients of ITER for three groups throughout three proximity thresholds. For the threshold of 100 km, the results show that the coefficient estimate of ITER increases with the ownership level of home-biased funds. This increasing pattern is more strongly represented when the threshold is increased to 500 km. Consistent with our prediction, these results confirm that the tail risk premium of REITs is positively associated with the ownership size of home-biased shareholders. On the other hand, the results of the 1000-km threshold show that these increasing patterns disappear, and the coefficient estimates are comparable across the three groups. This suggests that the definition of home bias may not work if the distance threshold of overweighted investment is up to 1000 km, which can cover several states.

[12] We obtain the historical location of mutual funds from annual N-SAR filings and contact information of the CRSP mutual fund database, similarly to Pool et al. (2012) and Giannetti and Laenven (2016). We obtain historical headquarters location from 10K filings and historical header files of the COMPUSTAT-CRSP-merged database (see Bernile et al., 2015)

TABLE 13 Impacts of home biased investors

Dependent variable: $r_{i,t+1}$	Distance theshold of Coval and Moskowitz (2001) home bias measure		
	100 km (1)	500 km (2)	1000 km (3)
Low	0.099	0.091	0.163
	(1.48)	(1.15)	(1.44)
Medium	0.168**	0.151**	0.134**
	(2.59)	(2.06)	(2.16)
High	0.226**	0.354***	0.130*
	(2.11)	(4.52)	(1.82)

Note: This table presents regression coefficients of ITER based on the Fama–Macbeth (1973) regression with full control variables using the three subsamples sorted by home-biased exposure measure. We used low (less than 30%), medium (higher than 30% and less than 70%), and high (higher than 70%) groups. Columns 1–3 report the coefficient estimates of ITER across three distance thresholds of the Coval and Moskowitz (2001) home bias measure from 100 to 1000 km.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6 | CONCLUSION

In this article, we propose a novel tail risk measure, ITER, which captures tail exposure risks from multiple industries. Throughout various empirical asset pricing tests, we find a significant return premium of ITER. REITs in the highest ITER group (Quintile 5) provide significantly future excess returns of 0.70% per month (8.40% per annum) more than REITs in the lowest ITER group (Quintile 1). The positive return premium remains even after controlling for various firm characteristics. In particular, the return premium is larger for small-, value-, and high-levered REITs. The results of Fama–Macbeth (1973) show that the slope coefficient of ITER with full control variables is highly significant, with Newey–West (1987) t-statistics above 3.0, which is a hurdle proposed by Harvey et al. (2016). The impact of ITER shows countercyclical behavior against economic activity, implying that REIT investors require a higher return premium during the market recession, in line with theoretical literature associated with time-varying risk aversion. We further document that the ITER predictability is stronger among REITs that have higher BTER with major industries, register higher local tail risk and geographical concentration and are more exposed to home-biased investors. Overall, our novel measures "ITER" empirically demonstrate that joint tail events with various industries are an important source of tail risk premiums.

ACKNOWLEDGMENTS

We thank Lu Han (the editor) and an anonymous referee for constructive comments and suggestions. We also acknowledge helpful comments from Kian Guan Lim, Cristian Badarinza, Graeme Newell, Tien Foo Sing, and seminar participants at the National University of Singapore.

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How to cite this article: Song, J., & Liow, K. H. (2022). Industrial tail exposure risk and asset price: Evidence from US REITs. *Real Estate Economics*, 1–37.
https://doi.org/10.1111/1540-6229.12402