Uncertainty measures and sector-specific REITs in a regime-switching environment

Abstract

In this paper, we attempt to explore the effects of various uncertainty measures – namely, implied volatility (VIX), tail risk (SKEW), economic policy uncertainty (EPU) and partisan conflict (PCI) indices, on U.S. REITs returns at sector level, using the non-linear Markov regime-switching model. Our empirical results reveal that uncertainty measures have regime-dependent impacts and do not affect the return dynamics of REIT sectors in a uniform way. Office and hotel & lodging REITs exhibit the strongest sensitivity to VIX and EPU, respectively, during bearish market periods. While residential REITs are the most resilient to uncertainties, healthcare REIT returns are negatively affected from all the uncertainty factors only in the low variance regime. Hence, our findings show evidence of asymmetric, non-linear and sector-dependent linkages between REITs and uncertainties. These results provide valuable insights and important implications for REIT investors.

Keywords: REITs, uncertainty, Markov regime-switching, implied volatility.

Paper type: Research paper.

1 Introduction and Motivation

Understanding how uncertainty affects financial markets is of utmost importance for investors, portfolio managers and policy makers. Several indicators, such as the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) and the CBOE Skew Index (SKEW), have been traditionally used in practice to capture uncertainty over the market sentiment. Even though it is hard to find an exact measure of uncertainty because uncertainty is inherently a latent variable (Chuliá et al., 2017), the latest developments in the literature help us numerically quantify different forms of uncertainty. Recently, news-based indices have gained considerable popularity in many applications in the fields of economics and finance. Baker et al. (2016) has introduced an Economic Policy Uncertainty (EPU) index, which reflects regulatory, monetary, and fiscal policy uncertainty. A burgeoning literature has been devoted to analysing the links between EPU and financial markets – particularly, stock returns (see, for instance, Arouri et al., 2016; Belke et al., 2016; Kido, 2018; Albulescu, 2019; Das et al., 2019; Su et al., 2019; Zhang et al., 2019; Goodell et al., 2020, among others). More recently, Azzimonti (2018) has constructed a novel Partisan Conflict Index (PCI) to measure the degree of political disagreements among U.S. politicians. Increases in PCI are associated with greater uncertainty about which policies politicians will choose – that is distinct from uncertainty related to existing government policies generated by EPU shocks (Cheng et al., 2016).

Modern Finance Theory has proposed a number of metrics to quantify risk. Early work of Markowitz (1952) introduced a portfolio theory in which a risk-averse investor can optimize the expected return of a portfolio, given a level of risk that is measured as the variance of portfolio returns. Building on Markowitz's Portfolio Theory, Sharpe (1964), Lintner (1965), and Mossin (1966) developed the Capital Asset Pricing Model (CAPM) that describes the relation between risk and expected return, implying that investors are compensated for bearing systematic risk, that is measured by beta. The CAPM marks the birth of asset pricing theory and modern asset pricing models have evolved from one beta to multifactor beta. Fama and French (1992) proposed a model that expands on the CAPM by adding two new factors (namely, size and value factors) to the market risk factor. All these developments in the asset pricing literature have helped researchers analyse the relationship between risk and return; however, they do not allow us to distinguish between risk and uncertainty. Long before the development of modern portfolio theory, Knight (1921) formalized the distinction between risk and true uncertainty and conceptualized uncertainty as the situation in which economic agents cannot properly evaluate the probability distributions of future outcomes.[1] He defines risk as the condition in which all potential outcomes are a priori unknown, but their likelihood of occurrences is perfectly known. Therefore, Knightian uncertainty is a broader concept than risk and incorporates ambiguity about the parameters of the probability distribution. Uncertainty in the sense of Knight (1921) has been present in the literature for a long time; however, academic studies have mostly treated it purely descriptively until researchers found methodologically sound techniques to quantify it (Perić and Sorić, 2018).

Although it is hard to quantify Knightian uncertainty, news-based uncertainty indices, including EPU and PCI, can capture it (Lolić et al., 2021) as they measure unobservable underlying components of uncertainty. SKEW and VIX indices are also based on the idea of Knightian uncertainty, because they can be decomposed into components that reflect uncertainty and a risk premium (Bekaert et al., 2013).[2] Even though theoretical work on the impact of uncertainty on the macroeconomy dates back to Bernanke (1983a), our understanding of how uncertainty factors affect asset prices is limited due to the lack of theoretical guidance and models in which financial markets react to uncertainties are absent from the mainstream theory (Pástor and Veronesi, 2013). Nevertheless, recent studies, including Pástor and Veronesi (2012, 2013), have developed theoretical models that explain the response of asset prices to uncertainties and provided asset pricing implications. In the existing literature, there have been numerous attempts to empirically examine the relationship between various uncertainty measures and financial assets, such as stocks (Brown and Cliff, 2004; Giot, 2005; Sarwar, 2012; Bekaert and Hoerova, 2014; Sarwar, 2014, Arouri et al., 2016; Das et al., 2019), bonds (Connolly et al., 2005; Miyajima, et al., 2015; Naifar et al., 2017; Balli et al., 2020), currencies (Cairns et al., 2007; Kido, 2016; Al-Yahyaee et al., 2020; Papadamou et al., 2021) and commodities (Wang et al., 2015; Shahzad et al., 2017; Bilgin et al., 2018; Gozgor et al., 2018; Chaudhry and Bhargava, 2020; Zhu et al., 2020). However, surprisingly, very few studies have analysed to what extent uncertainty factors affect real estate investment trusts (REITs) (for example, Philippas et al., 2013; Ajmi et al., 2014; Akinsomi et al., 2016; Anoruo and Murthy, 2017; Shen, 2020), despite the fact that REITs have become an important part of the investment universe with $1.2 trillion total equity market capitalization and $3.5 trillion in gross real estate

[1] Nevertheless, "risk" and "uncertainty" are used interchangeably in the literature and studies often tend to view these two concepts as equal.

[2] The risk premium component of VIX and SKEW indices reflects variance premium and skewness risk premium, respectively.

assets as of 2020.[3] Most of the aforementioned REITs studies focus on the effects of VIX as it is the oldest benchmark index to measure market uncertainty and there is no comprehensive study in the literature that examines the links between various forms of uncertainty and REIT returns.

Against this backdrop, the primary objective of this paper is to explore the impacts of four different uncertainty measures, namely SKEW, VIX, EPU and PCI, on U.S. equity REIT returns at the sector level by controlling for asset pricing factors (the Fama-French three-factor model variables and momentum effect) and macroeconomic variables. As suggested by Hoesli and Oikarinen (2012), the use of a broad REIT index may mask important sector-specific information as the REIT indices differ significantly with respect to the property types. Indeed, previous studies (e.g., Reddy and Cho, 2018; Van Nieuwerburgh, 2019) have shown varying degree of business cycle exposure across REIT sectors. Each REIT sector has unique characteristics, distinct demand and supply drivers and responds to economic factors in different ways. For example, hotels & lodging REITs that have short-term lease durations are one of the most cyclical sectors, while apartments that have a more stable and diversified demand base are less reliant on business cycle shift (Anderson et al., 2003). Wheaton (1999) suggests that "real estate certainly does not behave uniformly as a single sector within the economy"; some properties, such as industrial space, tend to have higher correlation with the economy, whereas other REIT sectors, such as retail properties, have little relationship to the economy. He further reports that the only common component among property types is a high degree of asset durability – however, supply and demand elasticities vary significantly across real estate sectors. Moreover, REIT sectors offer opportunities for portfolio diversification and help investors reduce the risk associated with individual REITs. The growth of non-traditional REITs, such as healthcare, self-storage and timber, has transformed the real estate sector by allowing institutional investors to expand their focus beyond traditional REITs and derive income from highly distinct assets (Newell and Wen, 2006). Therefore, investment managers classify equity REITs into property types when measuring performance and making investment decisions (Anderson et al., 2015). In addition, major data providers such as the National Association of Real Estate Investment Trusts (NAREIT) categorize REITs by property type as well (Young, 2000). Given the heterogeneity across REIT sectors, we focus on sectoral REIT indices and the aggregate REIT index, and we conjecture that uncertainty measures may have heterogenous effects on REIT returns.

We employ both linear regression and non-linear Markov regime switching regression (MRS) models to investigate the impacts of uncertainty factors on sector-specific REITs. Previous scholarly work provides evidence of the regime-switching dynamics of REITs, suggesting that the return performance of securitized real estate investments significantly changes with respect to market states (Wilson, 2004; Chen and Shen, 2012; Lizieri et al., 2012; Case et al., 2014). Bianchi and Guidolin (2014) further report that REIT returns are characterised by bear and bull market states which can be best captured by the MRS models. Given the state dependent behaviour of REIT returns, the effects of uncertainty measures on REITs might significantly differ under diverse market conditions. Moreover, our sample period of almost thirty years from January, 1990 to October, 2020 witnesses important social and

[3] The statistics were taken from the National Association of Real Estate Investment Trusts (NAREIT) website which is available at https://www.reit.com/data-research/data/reits-numbers.

economic events, such as financial crises, recessions and the unfolding COVID-19 pandemic, which makes the use of MRS model even more vital.

There has been an increasing number of studies investigating the impacts of uncertainty factors on stock returns in recent years. Even though the literature reports mixed results regarding the association between uncertainty measures and stocks, the consensus is that uncertainties can be important in explaining variations in equity prices (Sarwar, 2012; Brogaard and Detzel, 2015; Kang et al., 2017; Phan et al., 2018; Cheuathonghua et al., 2019; Kyrtsou et al., 2019). However, the results for the effects of uncertainty factors on stocks may not hold for REITs due to the prominent differences between the two. For instance, although both stocks and REITs can offer a steady stream of income for financial market participants, they differ in terms of dividend policy and tax status. While REITs are required to pay out 90% of their income to shareholders in the form of dividends every quarter, some stocks do not have to pay any dividends at all in the U.S. market. In addition, as known, common stocks are subject to double taxation, whereas REITs do not pay any corporate income taxes and only shareholders are taxed at personal taxation rates. Furthermore, REITs are considered as an inflation hedge as opposed to stocks and they tend to be more sensitive to interest rate changes (Zhang and Hansz, 2019). Therefore, uncertainty factors may not affect REITs in the same way due to their unique characteristics.

Uncertainties can impact REITs through several channels. Given that REITs are companies that own, manage, and operate income-generating real estate in a wide range of property sectors such as offices, apartments and shopping malls, any shock to the underlying real estate sector can significantly affect securitized REITs. The existing literature also suggests that REITs and the underlying real estate are tightly linked (Brounen et al., 2000; Jackson, 2009; Boudry et al., 2012). According to Bernanke (1983b) and Bloom et al. (2014), individuals tend to respond to uncertainty by decreasing consumption of durable goods. In periods of heightened uncertainty, households may delay their consumption decision and increase their precautionary savings amid concerns about future income and employment (Giavazzi and McMahon, 2012). On the other hand, increased uncertainty might prompt lenders and mortgage providers to reduce or deny mortgages to risky borrowers due to higher default risk and higher cost of financing (Choudhry, 2020). Consequently, a decreasing demand and plummeted prices in direct real estate markets can negatively affect securitized REIT returns. However, we should not rule out positive impacts of uncertainties. For example, El-Montasser et al. (2016) note that higher uncertainty may result in higher demand for housing, which increases house prices, if other financial assets are more sensitive to uncertainty and housing is seen as relatively safer investment. Besides, as stated by Bilgin et al. (2018), the impacts of uncertainty measures on asset prices can be either negative or positive, depending on the market conditions. Moreover, the effects of uncertainties on REITs can be linked to irrational market sentiment. Shiller (2007), for example, claims that it is not possible to explain the housing bubble in 2005-2006 by economic fundamentals but instead non-fundamental psychological factors played an important role in driving the prices. Given the abundance of empirical evidence showing potential investor irrationality and herding behaviour in the REIT market (see, Lin et al., 2009; Zhou and Anderson, 2013; Das et al., 2015, among others), it is not unexpected that behavioural biases can mislead REIT investors' decision-making process – particularly in times of high uncertainty or crisis. This may lead prices to fluctuate more than fundamentals and result in noise traders mispricing investments (Jin et al., 2014).

As stated earlier, the effects of uncertainty factors on equity REITs have not received much attention in the literature. Most of the relevant studies focus on housing market returns (see, Antonakakis et al., 2015; El-Montasser et al., 2016; Bahmani-Oskooee and Ghodsi, 2017; Ngene et al., 2017; Huang et al., 2018; Bekiros et al., 2020; Choudhry, 2020, among others). Nevertheless, there are very few papers exploring the impacts of uncertainties on REITs. For example, Ajmi et al. (2014) investigate the link between U.S. REIT index and uncertainty shocks and find that both policy-induced uncertainty and investor sentiment (VIX) measures are important in explaining REIT returns. In a more recent study, Shen (2020) analyses the links between distress risk and equity REIT returns and documents that movements in VIX, together with institutional ownership on the REITs, can explain the distress anomaly in the REIT market. Exploring herding behaviour in U.S. equity REITs at the sector level, Philippas et al. (2013) report that the deterioration of investors' sentiment, measured by an increase in the implied volatility index (VIX), is negatively related to the dispersion of REIT returns. A similar finding is also reached for the U.K. market by Akinsomi et al. (2018) who provide evidence that general stock market uncertainty, proxied by the U.K. VIX, may be a source of increasing herding-related risks among U.K. REITs. From a different viewpoint, Huang and Wu (2015) and Huang et al. (2016) investigate the determinants of tail dependency between REITs and stocks. Their overall results reveal that VIX is one of the significant explanatory variables, implying its forecasting ability. As documented, the majority of relevant studies focus on investor sentiment (measured by VIX) and ignore the potential impacts of other uncertainty factors such as policy-induced uncertainty, political risk or tail risk. Accordingly, our paper attempts to fill this gap by answering several research questions. More specifically, we focus on the following three main questions: (i) How do various forms of uncertainty affect REIT returns in a linear fashion? (ii) Do uncertainty factors have state-dependent impacts on REITs? (iii) Considering the sectoral heterogeneity, which REIT sector is the most (least) vulnerable to uncertainties?

Our paper differs from most prior work by investigating the impacts of four uncertainty measures on REITs returns at the sector level. To the best of our knowledge, this is the first study in the literature that comprehensively examines the effects of various uncertainty factors on REIT sectors' returns. More specifically, we contribute to the existing literature in several aspects. First, uncertainty measures used in this study reflect different types of uncertainties that can significantly affect financial markets. VIX and SKEW are investor sentiment measures, however they differ in that VIX captures overall market volatility, while SKEW quantifies perceived tail-risk in the S&P 500. EPU index measures fiscal, regulatory, or monetary policy uncertainty and has a considerable impact on economic and financial fundamentals (Phan et al., 2018). PCI measures the frequency of newspaper articles reporting political disagreement about government policy, which gauges the degree of political uncertainty in the U.S. (Bouoiyour et al., 2018). Therefore, in this study, we analyse the impacts of various uncertainty indicators, from aggregate market uncertainty measures to political risk, and provide empirical findings that can be of paramount importance for traders in the REITs market.

Second, our study underscores the importance of investigating the impacts of uncertainty measures on REITs at the sector level. Our empirical findings suggest that the impact of uncertainties is heterogeneous across REIT sectors, which implies that uncertainties do not affect the return behaviour of REITs in a uniform way. The results reveal that hotel & lodging (office) REIT is the most vulnerable to EPU (VIX), whereas residential REITs index is the most resilient to uncertainty-induced shocks. Tail risk, measured by SKEW index, has marginal effects on a few REIT sectors and a high degree of political disagreement, proxied by PCI, can cause significant drops in REIT returns for specific sectors, such as healthcare and speciality. Therefore, as suggested by Hoesli and Oikarinen (2012), utilizing aggregate data may mask valuable sector-specific information, however, sector level data can give more accurate and reliable results regarding the influence of uncertainty measures.

Third, we employ the non-linear Markov regime switching (MRS) model to investigate the response of REITs to uncertainty measures. The use of MRS models allows us to analyse the asymmetric effects of uncertainty factors during market upturns and downturns. As noted in Case et al. (2014), surprisingly, relatively fewer research has employed the MRS model to explain the behaviour of REIT returns (Liow et al., 2005; Liow and Zhu, 2007; Chang et al., 2011; Chen and Shen, 2012; Lizieri et al., 2012; Anderson et al., 2012; Fatnassi,et al., 2014; Liow and Ye, 2017). Hence, we also add to the existing body of knowledge in the real estate finance literature by modelling REIT returns in a regime-switching framework. The results provide evidence of state-dependent impacts of uncertainty indicators on REITs. For example, the MRS model and asymmetry tests suggest that healthcare REIT returns are significantly sensitive to all uncertainty measures, but only in low volatility regime. Office and hotel & lodging REITs display strong negative reaction to VIX and EPU, respectively, only when the market enters bear market territory. The main findings demonstrate significant asymmetric dependence of REIT returns to uncertainty factors under changing market conditions. We discuss potential implications of the empirical results in the findings and conclusion sections.

The remainder of the paper is as follows. Section 2 and 3 present the description of the data and the methodology, respectively. Section 4 presents the empirical results for the linear regressions and non-linear MRS models and provides discussion. Finally, Section 5 concludes the paper and discusses potential implications of the empirical findings.

2 Data Description and Summary Statistics

Our dataset consists of monthly data for the sectoral REIT indices and explanatory variables, covering the period from January, 1990 to October, 2020.[4] We compute the continuously compounded returns for each REIT index as $R_{i,t} = (\ln P_{i,t} - \ln P_{i,t-1}) \times 100$, where $R_{i,t}$ is the return of the index i in month t; $P_{i,t}$ is the price of the index i in month t and $P_{i,t-1}$ is the previous month's (t-1) price of index i.

Table 1 summarises the REIT indices, explanatory variables, uncertainty measures, their sources and explanations. We investigate nine sectoral REIT indices and the composite REIT index and obtain the REITs data from Datastream.[5] The sectoral REIT indices used in this study are the most common and cover almost 75% of the equity REITS (see, Newell and Wen, 2006; Hoesli and Oikarinen, 2012; Philippas et al., 2013; Lin et al., 2019, among others). We use asset pricing factors and various economic indicators as control variables. We obtain market risk premium, size factor (Small minus Big), value factor (High minus Low) and momentum from

[4] The VIX and SKEW indices are available from January 1990, that is why our sample starts from that date.

[5] In this study, we do not focus on diversified and infrastructure REITs since their sample period starts from January 1998 and June 1998, respectively.

Kenneth French's online data library.[6] Some relevant studies have found that the three-factor model with some additional factors such as term premium and momentum can significantly explain variations in REIT returns[7] (Lin et al., 2009; Ro and Ziobrowski, 2011; Jackson, 2020). Following Hoesli and Reka (2015), we use the credit spread and the term spread as business cycle proxies. Other macroeconomic variables include industrial production, unemployment rate and inflation as they are the most used in the existing literature (see, for example, Naranjo and Ling, 1997; Payne, 2003; Ewing and Payne,2005; Glascock and Lu-Andrews, 2014; Kola and Kodongo, 2017). All the macroeconomic variables are extracted from the Federal Reserve Bank of St. Louis.

(Insert Table 1 about here)

Finally, we select four uncertainty measures, which are the main focus in our study. These measures have been used by scholars, as a proxy of uncertainty, to measure the effect of non-fundamentals on various financial assets (e.g., Bilgin et al., 2018; Jiang et al., 2020). The detailed explanations of each measure are as follows:

- *Economic Policy Uncertainty (EPU) Index:* Baker et al. (2016) construct the U.S. EPU index based on three components: news coverage about policy-related economic uncertainty, tax code expiration data and economic forecaster disagreement. The news coverage component consists of ten large newspapers, such as the Washington Post and the Wall Street Journal, containing search terms related to economic and policy uncertainty. The tax code component uses the Congressional Budget Office (CBO) reports to calculate annual dollar-weighted numbers of federal tax code provisions set to expire over the next 10 years. The last component reflecting the disagreement among economic forecasters draws on the Survey of Professional Forecasters conducted by the Federal Reserve Bank of Philadelphia and uses the measures of forecast dispersion about inflation and expenditures. The EPU index is available at https://www.policyuncertainty.com/. Figure 1 (a) displays the time evolution of the EPU index and shows that the index successfully captures important events. Sudden spikes in policy uncertainty coincide with major incidents, such as 9/11 terrorist attack and the collapse of Lehman Brothers in September 2008. The EPU index records the highest increase with the announcement of the World Health Organization (WHO) declaring COVID-19 a global pandemic on March 11, 2020.

- *Partisan Conflict Index (PCI)*: Azzimonti (2018) uses a semantic search-based method to build the PCI by counting the frequency of newspaper articles published in major U.S. newspapers, such as the Washington Post and the New York Times, reporting disagreement between politicians about government policy. As explained by Azzimonti (2018), the index is constructed by specifically focusing on newspaper articles that contain at least one keyword in

[6] For further information about the definition and construction of the three-factor model and momentum factor, you can refer to Fama and French (1992) and Carhart (1997). The factor variables are available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[7] We also consider the Fama-French five-factor model which adds two new factors, namely investment and profitability factors, to the three-factor model. However, untabulated regression results show that these new two factors are not significant in explaining the REIT returns; therefore, we proceed with the three-factor model. The regression results for the five-factor model are available upon request. For further information about the five-factor model, you can refer to Fama and French (2015).

two categories: (i) political disagreement and (ii) government. More specifically, the search includes terms related to partisan conflict, the political debate, and the partisan warfare. Figure 1(b) exhibits the PCI and clearly suggests that the partisan conflict increases after the global financial crisis of 2008 and reaches the highest values during the United States federal government shutdown in October 2013, the 2016 Presidential election and Donald Trump's first two months in office. The PCI scores are lower at certain times, such as Afghanistan and Iraq wars in 2001 and 2003 and COVID-19 pandemic, due to the "rally around the flag" effect, suggesting that wars and international crises bring about short-run popular support of the government and greater stability of party control. The PCI index is downloaded from https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/partisan-conflict-index.

- *The Chicago Board Options Exchange (CBOE) SKEW Index (SKEW):* Given the stylized fact of the non-normal distribution of S&P 500 log returns, there is always the implied likelihood of tail risk, indicating that the frequency of extreme returns is greater than for a normal distribution and the return distribution is negatively skewed. In order to fully capture the perceived tail risk, the CBOE introduced a new indicator called SKEW. The Skew Index is a gauge of perceived tail-risk in the S&P 500 and sometimes referred to as "Black Swan" index. In other words, it measures the risk of extreme negative movements in the U.S. stock markets (Gozgor, 2014). It is calculated using out-of-the money S&P 500 options' prices and its values typically range from 100 to 150. A SKEW level of 100 shows that the distribution of S&P 500 returns is normal and hence the likelihood of an outlier return is small. Figure 1 (c) plots the SKEW index. It is evident that the index has an upward trend after 2008, suggesting an increasing demand for tail-risk hedging. We also observe sudden spikes around the U.S. 2016 elections and the beginning of the pandemic, which shows that the SKEW index successfully reflects the market volatility and changes in investor sentiment.[8]

- *The Chicago Board Options Exchange (CBOE) Volatility Index (VIX):* VIX is a well-known measure of market volatility and closely followed by financial market participants as an indicator. Similar to the SKEW index, it is calculated using the S&P 500 options' prices, however the main difference is that the VIX considers implied volatility of at-the-money options. VIX, as a measure of standard deviation, reflects the first layer of perceived risk while the SKEW index captures the additional layer of risk implied by the left tail of the log-return distribution. VIX is also often referred to as Wall Street's "fear gauge" since volatility is seen as a way to measure investor sentiment, and the degree of fear among investors. Figure 1 (d) displays the evolution of VIX and shows that the index significantly increases during periods characterized by high uncertainty. It reaches its highest value during late 2008 marked by the collapse of Lehman Brothers, a value closely followed by the global spread of coronavirus in the second half of 2020.

(Insert Figure 1 about here)

[8] For further information about the construction of the SKEW index, you can refer to the white paper published by the CBOE, which is available at: https://cdn.cboe.com/resources/indices/documents/SKEWwhitepaperjan2011.pdf.

Table 2 presents the descriptive statistics for each REIT index.[9,10] Looking at the mean values, we see that the storage (hotel & lodging) index has the highest (lowest) monthly average returns. In terms of unconditional volatility measured by standard deviations, hotel & lodging index is the riskiest while speciality index returns carry the lowest risk. The skewness statistics are all negative, indicating that getting a negative return is more likely than getting a positive return for all the REIT indices over the sample period. The kurtosis values are all higher than three predicted by normal distribution, showing that REIT investors may experience occasional extreme returns. Therefore, both measures of higher moments imply that REIT returns exhibit leptokurtic distributions with skewed fat tails.

(Insert Table 2 about here)

We further examine the existence of potential non-linearity in each REIT index, applying the BDS test introduced by Broock et al. (1996). This is a popular and widely used test for the presence of nonlinearity in time series. The BDS test has a null hypothesis that a time series comes from a data generating process which is independent and identically distributed (i.i.d.) for combinations of ε (value for close points) and m (embedding dimension). Epsilon (ε) denotes the probability of the distance between a pair of points to measure the i.i.d residuals while embedding dimensions stand for the number of consecutive data points used in the set of pairs chosen (Uddin et al., 2018). Table 3 shows the test statistics and the associated bootstrap *p*-values. The results demonstrate that the null hypothesis is rejected for all the combinations of ε and m at the conventional significance levels, except for a few cases. For healthcare, storage and timber indices, although the results are sensitive to the choice of ε and m, we still find statistical evidence of nonlinear structures. Therefore, the BDS tests suggest potential existence of nonlinearity in the data, indicating that a linear model fitted to the REIT returns can be misspecified.

(Insert Table 3 about here)

3 Linear Model and Markov Regime Switching

In this study, we first analyse the linear relationship between uncertainties and REITs and then we employ Markov regime-switching model of Hamilton (1989) to account for potential non-linear dependence between REIT sector returns and uncertainty measures. As documented by prior work (Chen and Shen, 2012; Anderson et al., 2012; Case et al., 2014; Liow and Ye, 2017), REITs display regime-dependent return behaviour, which implies that the assumption of linearity to model REIT returns may lead to misspecified and biased conclusions. The MRS model fully allows for regime-specific volatilities and distinguishes between different market states (Babalos et al., 2015). It can easily capture non-linearity and asymmetry present in the relationship between economic and financial variables as it allows model coefficients to switch between different market states (e.g., bull and bear markets). Studies employing the MRS

[9] For the sake of brevity, we do not report summary statistics of explanatory variables and uncertainty measures, however they are available upon request.

[10] Note that our linear and non-linear approaches require stationarity. We test for stationarity using the augmented Dickey–Fuller and Phillips–Perron unit root tests. The test results show that the return variables, asset pricing factors and uncertainty measures do not contain unit-root; therefore, as suggested by Hoesli and Reka (2015), these stationary variables do not need to be transformed before the model estimations. All the macroeconomic factors are non-stationary, that is why we use the first difference of these variables. The unit-root test results are not reported here, but they are available upon request.

models make the major distinction across the bear and bull markets relating to the level of market volatility and the sign of returns. For example, Case et al. (2014) investigate the Markov switching dynamics in REIT returns and state that high volatility regime represents a bear-market state with low excess returns, while low variance regime represents a bull-market state with relatively high excess returns. Therefore, our regime specification is consistent with the market characterization (bear versus bull) of relevant studies (see, Akinsomi et al., 2018; Babalos et al., 2015; Bianchi and Guidolin, 2014; Chou and Chen, 2014; Liow and Ye, 2018; Liow and Zhu, 2007, among others). The MRS approach is particularly useful in our case enabling us to estimate separate regime-dependent coefficients since we analyse the effects of explanatory variables on REITs across different regimes. Furthermore, Arouri et al. (2016) suggest that the MRS model accounts for possible regime changes and structural breaks that can create varying regimes of uncertainty. This point is very important for our study, because our sample period includes important events such as the subprime mortgage crisis and the unfolding coronavirus pandemic, which may significantly affect REIT returns – in fact, the BDS test results presented in Table 3 confirm potential existence of non-linearity in the REIT return dynamics.

Following Hoesli and Reka (2015) and Van Nieuwerburgh (2019), we adopt a multifactor model. As discussed earlier, alongside Fama-French three-factor variables, momentum and uncertainty indicators, we include macroeconomic factors in both linear and nonlinear MRS models. Before applying the MRS model, we first employ the linear baseline multifactor model which has the following form:

$$R_{i,t} = \alpha + B\ UNCERTAINTY + \Gamma\ CONTROL + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the excess return on a given REIT sector index, *UNCERTAINTY* and *CONTROL* represent a vector of uncertainty measures and control variables (e.g., asset pricing factors and macroeconomic variables). α denotes the intercept and $\varepsilon_{i,t}$ is the error term. β coefficients in the vector B measure the sensitivity of each REITs sector returns to uncertainty indicators and γ coefficients in the vector Γ quantify the exposure to asset pricing factors and macroeconomic variables. We use a heteroscedasticity and autocorrelation (HAC) consistent covariance estimator, known as the Newey-West estimators, in the baseline regressions to generate robust standard errors.

The MRS model allows the impacts of explanatory variables on REITs to differ across market states (S_t). Eq. (1) can be reformulated for the MRS framework as given below:

$$R_{i,t} = \alpha + B_{S_t}\ UNCERTAINTY + \Gamma_{S_t}\ CONTROL + \eta_{i,t} \tag{2}$$

where $\eta_{i,t}= iid(0, \sigma^2_{st})$ is the model error term and $S_t= \{1, 2\}$ is an unobservable state variable governed by a first-order Markov process, which evolve according to the transition probabilities as shown below:

$$p = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} \tag{3}$$

where,

$P[S_t = 1 | S_{t-1} = 1] = p_{11}$, $P[S_t = 2 | S_{t-1} = 1] = p_{21} = 1 - p_{11}$.

$P[S_t = 2 | S_{t-1} = 2] = p_{22}$, $P[S_t = 1 | S_{t-1} = 2] = p_{12} = 1 - p_{22}$.

where, P_{12} (P_{21}) represents the transitional probability that state 2 (1) will be followed by state 1 (2). P_{11} and P_{22} denote the probabilities of no change in the state of the market in the following period. Therefore, by construction, every row must sum up to unity.

In the MRS framework, S_t is assumed to depend only on the regime in the previous period S_{t-1}. Within our MRS specification, $S_t=1$ corresponds to the low volatility state (tranquil or bull market regime) and $S_t=2$ indicates the high volatility regime (bear market or crisis regime). The transition probabilities p_{11} and p_{22} denote the probabilities of staying in the low volatility regime and high volatility state, respectively, in the following period. The transition probability p_{12} (p_{21}) represents the probability that high (low) volatility regime is followed by low (high) volatility state. The expected duration of each regime can be obtained from the transition probabilities as given below:

$$D_{kk} = 1/(1 - P_{kk}) \tag{4}$$

where, D_{kk} gives the expected duration of the regime kk and P_{kk} represents the probability that the market stays in the same regime.

As suggested by Zhu et al. (2016) and Basher et al. (2018), a good-fitting MRS model provides distinct regime classification with smoothed state probabilities that are either close to zero or one. In order to determine the accuracy of the MRS models, we utilize the regime classification measure (RCM) proposed by Ang and Bekaert (2002) given as follows:

$$RCM = 100S^2 \times \frac{1}{T}\sum_{t=1}^{T}\prod_{k=1}^{S}\tilde{p}_{k,t} \tag{5}$$

where S denotes the number of regimes which is equal to two in our case and $\tilde{p}$ represents the average of the product of smoothed probabilities. The RCM gives an estimate of the variance since the switching follows a Bernoulli distribution. The RCM statistic ranges from 0 to 100; a value of 0 shows perfect regime classification while a value of 100 implies that the two-state MRS model assigns each regime a 50% chance of occurrence. Therefore, lower values of the RCM statistics indicate an overall well-fit of the MRS model. As suggested by Chan and Marsden (2014), a good-fitting MRS model has an RCM value lower than 50, which shows better regime classification.

Finally, we use a maximum likelihood optimization procedure to estimate the MRS model. Assuming Gaussian errors, $\eta_{i,t}$, the conditional density function for each state can be written as follows:

$$f\left(R_{i,t}|S;\Theta\right) = \frac{1}{\sqrt{2\pi\sigma_{S_t}^2}} exp\left\{-\frac{\left(R_{i,t}-\alpha-B_{S_t}\, UNCERTAINTY-\Gamma_{S_t}\, CONTROL\right)^2}{2\sigma_{S_t}^2}\right\} \tag{6}$$

where Θ stands for the vector of parameters to be estimated. Accordingly, the set of optimal parameters can be estimated by maximizing the log-likelihood function L which is a combination of the probability distribution of the state variable and the density function for each regime. The log-likelihood function is as follows:

$$L = \sum_{t=1}^{T} \log f\left(R_{i,t};\Theta\right) \tag{7}$$

4 Empirical Results and Discussion

4.1 Results from linear models

As stated earlier, regarding our first research question, we first estimate linear regression equations as the baseline models to investigate the effects of uncertainty measures on sectoral REIT excess returns, controlling for asset pricing factors and macroeconomic variables. Table 4 presents the estimation results.

(Insert Table 4 about here)

Looking at the factor loadings, we see that all the coefficients are statistically significant at least at the 10% level, except for the momentum factor in case of residential and storage indices. This supports the findings of Peterson and Hsieh (1997), indicating that REITs excess returns are significantly correlated with the Fama-French three factors. All the systematic risk parameters are less than one, showing that the REITs carry lower systematic risk than the overall market portfolio. We observe that the timber index is the riskiest in terms of systematic risk, which is line with Piao et al. (2016) who attribute the highest market beta to the portfolio construction process. The timber REITs sector is dominated by only four companies, indicating the least diversification potential. We can also consider the market beta as exposure to the economic cycle. REIT sectors, such as hotels & lodging that are known to be highly cyclical have higher systematic risk exposure relative to sectors that are less sensitive to economic activity, such as storage, which is in line with Van Nieuwerburgh (2019). The size factors SMB (small minus big) suggest that all REIT sectors behave like small-cap stocks. The factor loadings on HML (high minus low) show that all REITs are value stocks with high book-to-market value ratios. Therefore, the factor loadings present consistent results with the existing literature, suggesting that REITs are typically considered as small value stocks (Lin et al., 2009; Ro and Ziobrowski, 2011; Van Nieuwerburgh, 2019). Furthermore, the exposure of REITs to the momentum factor is negative and, albeit, relatively small in magnitude. This, in part, presents consistent findings with Chui et al. (2003) and Derwall et al. (2009) who report significant momentum effects in REITs. The results also provide evidence of significant differences in the size and value exposures across REIT sectors; while hotels & lodging REITs have the highest exposures to size and value factors, some sectors, such as healthcare and storage, have relatively lower exposures, reflecting the heterogeneity of the REIT sectors.

Considering the macroeconomic factors, our results reveal that industrial production, inflation and term spread do not have any explanatory power on REIT excess returns. Unemployment seems to have positive and significant impacts, only on healthcare and office indices. Credit spread has a negative and statistically significant effect in more than half of the cases, as expected. Credit spread, as measured by the difference between long term corporate bonds and 10-year Treasury notes, reflects investor concern as financial market participants tend to flee from relatively risky corporate bonds to safer government assets in times of high uncertainty, causing lower treasury yields and higher yields offered by corporate bonds. Therefore, widening default spread may also lower stock returns due to the flight to quality effect. The non-significant effect of economic variables is somewhat in parallel to He and Ng (1994) who find that macroeconomic factors may lose their explanatory powers on the stock returns when firm-specific variables are added to the model. Analysing the impacts of macroeconomic variables on REITs at the sector level, Payne (2006) gives support to our findings, showing that REIT sectors' returns are detached from unexpected shocks in economic variables. Our results are also consistent with Chen et al. (1998), Payne (2003) and Kola and Kodongo (2018), suggesting that macroeconomic variables might not explain REITs returns.

As for the uncertainty measures, the estimated coefficients on SKEW are only significant in case of industrial REITs – the associated coefficient is surprisingly positive. The coefficients on VIX are all negative and statistically significant in six of the sectoral REITs and in composite REIT index. Therefore, the baseline regression results suggest that although tail risk does not seem to have significant effects on the REIT indices, an increase in the implied volatility, measured by VIX, is associated with a fall in REITs returns. We further notice that VIX does not have any significant impacts on healthcare, retail and timber REITs. The heterogeneous effects of uncertainty factors on REITs imply that their exposure to uncertainty varies significantly depending on the sector. The coefficients on EPU are all negative but statistically significant only in case of hotels & lodging and retail REITs with hotels & lodging index showing the highest sensitivity. Looking at the impacts of partisan conflict, we do not document any statistically significant effects. In a nutshell, the linear regression results show that, among the uncertainty measures, VIX seems to be the most influential one. This is in line with previous literature, reporting predictive power of VIX for forecasting REIT returns (Huang et al., 2016; Anoruo and Murthy, 2017; Bekiros et al., 2020). Based on the magnitude of the statistically significant coefficients, we observe that the hotels & lodging REITs bear the greatest risk exposure to uncertainty measures, particularly to VIX and EPU. Therefore, as suggested by Reddy and Cho (2018), hotel and lodging REITs can be considered less suitable for risk-averse investors due to the cyclical nature of the business.

The R^2 values range from 16.2% to 39.8%, demonstrating that the explanatory variables included in this study do not explain a substantial portion of the returns of the REIT indices during the entire sample period. Low R^2 statistics may imply violation of the linearity assumption or model specification bias, showing the existence of a potential nonlinear relationship between dependent and independent variables not detected by the linear baseline regressions (Uddin et al., 2018). For this reason, we proceed with Markov switching models in the next section to capture possible non-linear effects.

4.2 Results from Markov regime-switching models

To address our second research question, we estimate the Markov regime switching models, with the assumption of having two volatility regimes, to examine any non-linear effects of uncertainty factors on REIT returns. Table 5 presents the estimated regime-dependent coefficients.

(Insert Table 5 about here)

The sigma coefficients, which are volatility estimates measured by the standard deviation for each regime, clearly show the existence of two regimes in REITs markets as the relevant coefficients in all regime specifications are statistically significant at the 1% level. The states in the MRS models are typically sorted into low and high volatility regimes: low (high) sigma coefficients imply low (high) volatility regimes. More specifically, low volatility regime captures relatively tranquil or bull market periods, while high volatility regime captures bearish market conditions or crisis periods. All sigma coefficients in the high volatility regime are higher than those of low volatility regimes. For example, in the case of healthcare sector, the estimated sigma coefficient in the high volatility regime is almost seven times higher than that in the low variance state, demonstrating a clear rejection of a single regime. Therefore, a two-state regime switching model is an adequate model to identify bull and bear markets for financial returns that tend to be cyclical, which supports the findings of Maheu et al. (2012).

Even though our main focus is to examine the asymmetric effects of uncertainty measures on sectoral REIT returns, we still provide a brief discussion about the state-dependent impacts of asset pricing factors and macroeconomic variables based on the coefficient estimates. Regarding the exposures to the asset pricing variables, our results reveal that all the Fama-French factors are state-dependent. We observe that the market risk factor is mostly positive and statistically significant at the conventional levels in both regimes, showing the presence of time-varying impacts of market risk.[11] This is in line with the findings of various empirical studies, reporting significant time-varying betas and market risk premiums, such as Brooks et al. (1998), Yao and Gao (2004) and Hoque and Zaidi (2019). The exposure to systematic risk factor is more pronounced in the high volatility regime in more than half of the sectors, which is somewhat consistent with Karlsson and Hacker (2013) who show that market risks tend to rise in times of crises and recessions. Wilson et al. (2004) further document that REIT investors require an extra premium, when the risk premium is high during bearish market periods. Moreover, the results suggest that factor loadings on SMB and HML are mostly significant in the low regime. In terms of the magnitude of the estimated coefficients, the SMB factors appear to be more useful than HML factors in explaining the REIT returns, particularly in the low regime, which partially supports the findings of Chiang et al. (2005). As for the momentum effect, most of the REIT indices have a negative exposure and this finding is in line with Ro and Ziobrowski (2011), Hoesli and Reka (2015) and Kizer and Grover (2017). Our results also provide evidence of regime dependent exposure of REITs to momentum factor, as the size of the coefficients changes across the sectors. The findings are somewhat in parallel to the recent study of Van Nieuwerburgh (2019), providing evidence of time-varying betas of equity REITs to asset pricing factors and of large economic differences between risk factors across REIT sectors.

The baseline regression results in the previous section show that macroeconomic factors, except for credit spread, do not significantly explain REIT returns. The MRS model provides a contrasting evidence that indicates state-dependent impacts of economic factors as some regime coefficients are strongly significant. Therefore, as stated earlier and shown by the BDS test results, the linearity assumption can give misleading results and biased conclusions. The estimated coefficients for industrial production are statistically significant in relatively few cases in both regimes and have mixed signs. There is still a weak evidence that REIT returns can be explained by changes in industrial production. When it comes to the impacts of the general price level though, we see that inflation is significant in most of the cases and increases in inflation have mostly a negative impact on REIT returns. The negative effect of inflation

[11] We should note a negative market premium on health care and office REITs in the low variance and high variance states, respectively. Pettengill et al. (1995) argue that when excess market returns are negative, relationship between beta and portfolio returns might be inverse. This contradicts with the positive risk-return trade-off predicted by the CAPM since the CAPM is based on expected rather than realized returns. Negative market premium is also documented for REITs markets. For example, Glascock and Lu-Andrews (2018) find that some REITs portfolios may experience negative returns when the realized market returns fall below risk-free rates. Sing et al. (2016) further show that market beta is asymmetric and time-varying, and some REITs are more sensitive to the shocks originating from the stock market in down-markets. We are grateful to the reviewer for bringing up this issue.

seems to be more pronounced in the high regime for health, retail and storage indices. Similar to industrial production, unemployment also has marginal effects on REITs as the estimated coefficients are mostly insignificant. However, rises in unemployment rate can lead to a significant fall in certain REIT sectors in different regimes; for example, healthcare in the low regime and timber in the high volatility state. Regarding the effects of credit spread and term premium, our results show that credit spread is more influential in the high variance regime in certain sectors, such as industrials and timber REITs, while the term spread has significant effects in relatively fewer cases. Overall, our results are in line with previous scholarly work, suggesting that the effects of macroeconomic variables on REITs are different across different phases of business cycle (Anderson et al., 2012; Glascock and Lu-Andrews, 2014). Therefore, REIT investors and portfolio managers should be aware of the state-dependent effects of macroeconomic fluctuations when making informed trading decisions.

Considering the effects of the SKEW index, the results reveal that the tail risk of the S&P 500 returns does not significantly explain REITs in the high volatility regime. We find statistically significant coefficients only in the low regime – in the case of health, retail and storage indices. While the healthcare and storage REIT returns are negatively influenced by an increase in SKEW index, the retail index has a more pronounced positive relation with the tail risk. Despite some statistically significant impacts in few cases, the probability of financial turmoil events, as measured by the fluctuations in the SKEW index, does not seem to have a strong influence on majority of the REIT indices. This is in line with DeLisle et al. (2013) who assert that REITs are neither sensitive to aggregate skewness nor idiosyncratic skewness. The non-significant impacts of the SKEW index can be attributed to the estimation error; for example, some studies, such as Liu and van der Heijden (2016) and Cao et al. (2019), document that the SKEW index can be very noisy, and the estimation error of true skewness calculated by following the CBOE SKEW method can be quite large. Furthermore, in a recent study, Bevilacqua and Tunaru (2021) empirically show that the SKEW index is related to extreme market movements reflecting the "unlikely". Therefore, we can state that REITs do not hold strong sensitivity to low-probability market events.

Looking at the estimated coefficients on VIX, we see that an increase in the so-called "fear gauge" index exerts statistically significant and negative impacts on REIT returns in at least one volatility regime for each sector, except for hotels & lodging, residential and timber REITs. Only in the case of retail index, the effect is positive in the low variance state. The results underscore the sectoral heterogeneity in REITs market as each sector displays different sensitivities to the measure of investor sentiment. For example, the office (healthcare) REITs bear the greatest risk exposure to VIX in the high (low) volatility regime, while hotels & lodging, residential and timber REITs indices appear to be the most resilient to the market measure of the short-term expected volatility in both regimes. Even so, the evidence shows that the impact of market uncertainty on certain REITs is economically significant and negative at varying magnitudes. Comparing this with the SKEW index, as stated by Whaley (2009), the VIX reflects investor sentiment on the expected volatility in the short term; hence, it is a market measure reflecting financial market events that are likely to happen (Bevilacqua and Tunaru, 2021). Liu and Faff (2017) further claim that the SKEW measure does not provide valuable information linked to VIX. Therefore, VIX appears to be more useful than SKEW in describing REIT returns. The significant link between VIX and REITs is further highlighted by other studies in the existing literature (e.g., Philippas et al., 2013; Huang and Wu, 2015; Huang et al., 2016; Anoruo and Murthy, 2017; Akinsomi et al., 2018).

Regarding the impacts of economic policy uncertainty, the state-dependent coefficients on EPU show that, similar to VIX, EPU has statistically significant effects on REIT returns in at least one volatility regime for the majority of the REIT sectors. This indicates that the baseline models without regime-shifting presented in Table 4 cannot correctly capture significant effects of media reference to economic policy uncertainty, as they give evidence of significant influence of EPU in only two cases. Industrial, residentials and composite REIT index returns are not significantly impacted by EPU-related news in both regimes, whereas hotel & lodging REITs are significantly more sensitive to EPU in the high volatility state than any other REIT sector in the sample. The estimated coefficients are mostly negative, except for storage and timber indices in the low regime, suggesting that increasing monetary policy uncertainty leads to lower REITs expected returns, which is consistent with studies reporting significant links between monetary policy and REITs (see, Ewing and Payne, 2005; Ajmi et al., 2014, among others). Our results further highlight that the impacts of EPU significantly vary depending on the volatility state, supporting the findings of Bredin et al. (2007) who document asymmetric responses of REITs to monetary policy shocks.

Lastly, the estimates of the coefficients on PCI show that partisan conflict has statistically significant effects on various REIT sectors across different volatility regimes – PCI has negative and significant impacts on industrial, retail, speciality, and storage indices in the high regime, while it seems to have a strong negative (positive) relationship with healthcare (storage) index in the low volatility state. Looking at the magnitude of the coefficients, healthcare index is the most sensitive to political disagreements in the low regime, followed by speciality index in the high regime. The negative effects of PCI imply that, as stated in Cheng et al. (2016) and Azzimonti (2018), when the politicians are polarized regarding economic policy, investors delay their investment decisions, thinking that the government will not be able to enact policies aimed at preventing adverse shocks. This may lower expected returns on investments and financial assets. Moreover, other indices in the sample, namely hotel & lodging, office, residentials, timber and the composite REIT index, are not significantly influenced by the number and frequency of media coverage of increasing polarization and divided government. Therefore, our results provide evidence of heterogeneous impacts of partisan conflict on REIT returns.

We also present regime statistics and asymmetry test results. Table 6 reports descriptive statistics for Markov-switching estimates and Figure 2 presents the smoothed probability plots of high volatility regimes and returns for each REIT index. The expected duration of being in a particular regime is measured in months and computed based on equation 4. The results show that, in most of the cases, the overall duration of the low volatility state is higher than that of the high volatility state, implying that turmoil or crisis periods have a lower duration than tranquil periods. In other words, the bear market periods tend to be shorter and much less persistent than bull market episodes. This supports the findings of Anderson et al. (2012), Chen and Shen (2012), and Bianchi and Guidolin (2014) who document high volatility regime is not as long-lived as low variance state in REITs. Again, we observe heterogeneous state-dependent characteristics of REIT returns; the average duration of the low variance regime ranges from a low of 1.04 months for healthcare to a high of 43.462 months for storage, while the average duration of the high volatility state varies from 1.250 months (residentials) to 22.104 months (industrials). As shown in Figure 2, there is some degree of commonality among some REIT indices as the patterns of smoothed high volatility regime probabilities are quite similar. Early 1990s recession, the global financial crisis of 2007-2009 and the unfolding COVID-19 pandemic appear to be the leading causes of high volatility in REIT markets. Therefore, the MRS model can successfully capture important events affecting REITs and it can provide insights for the identification of bear and bull market states for REIT returns.

(Insert Table 6 about here)

(Insert Figure 2 about here)

The diagonal entries of the transition probability matrix p_{11} and p_{22} represent the estimated probability of staying in low and high volatility regimes, respectively. Consistent with the expected durations above, the probability of staying in the low volatility state is highly persistent as the associated probabilities are above 0.8, except for healthcare and retail indices. For these two REIT sectors, interestingly, remaining in the bear market regime is more likely, as also evidenced by the regime plots given in Figure 2. The off-diagonal entries of the transitional probability matrix p_{12} and p_{21} denote the probability of switching from one volatility regime to another. For example, the probability of switching from high volatility regime in one period to low volatility state in the next, p_{12} is very high for residential and timber indices, implying that it is highly possible to observe a high volatility regime right before tranquil or bull market episode in these two REIT sectors. The final regime statistic, RCM is also reported for each REIT index in Table 6. Following Chan and Marsden (2014), we use a value of 50 as a benchmark; a RCM value below 50 shows a better regime classification. The results show that the RCM statistics range from 2.508 (storage) to 43.700 (residential), providing evidence of well-fitting Markov regime switching models for all the REIT indices in the sample. Nevertheless, the residential and timber indices have relatively higher RCM values as compared to the others, suggesting that the distinction between the regimes for the two is less clear, which is also shown by the relevant regime plots in Figure 2.

Table 7 presents the results for the Wald-type symmetry tests and reports the test statistics and associated *p*-values. The null hypothesis of the symmetry test is that uncertainty measures do not have any asymmetric impact on REIT returns. In this respect, the *p*-values that are lower than the 10% significance level lead us to reject the null hypothesis, providing evidence of asymmetry. The results suggest that the SKEW index has significant asymmetric effects on healthcare, retail and storage index returns at the 1% significance level. The test rejects the null hypothesis of symmetric impacts of VIX in majority of the cases at the conventional levels, except for hotels & lodging, residential and timber indices. For EPU, the evidence of asymmetry is found in more than half of the cases; industrials, office, residential and the composite REIT indices are not asymmetrically related to economic policy uncertainty. It is also worth-noting that the asymmetry is tested based on the magnitude of the regime-dependent coefficients; for example, even though EPU has a negative and statistically significant effect on office REITs only in the low regime, suggesting potential existence of asymmetry, the test results do not give any evidence of asymmetry since the coefficient is small in magnitude and slightly significant. Lastly, the null hypothesis of symmetric effects of PCI is rejected for four of the sectoral REITs, namely healthcare, industrials, speciality, and storage.

In overall, the symmetry test results confirm the MRS models in that the asymmetric impact of uncertainty measures is heterogeneous across REITs, implying that investor sentiment and news regarding economic policy changes and political uncertainty do not impact REIT returns in a uniform way. We further discuss the implications of (a)symmetries in the next section.

(Insert Table 7 about here)

4.3 Discussion

Employing the MRS model, we find significant asymmetries in REIT return dynamics according to the market state as volatilities significantly differ in the low and high variance states. Our results also provide evidence of state-dependent and heterogeneous effects of Knightian uncertainty measures on REIT returns. Tail risk measured by SKEW index is at play only during tranquil periods, while other uncertainty factors have significant heterogeneous effects across different REIT sectors in both high and low volatility states. As can be seen from Table 7, EPU and VIX have asymmetric effects on more than half of REITs. Also, sectoral REITs respond negatively to increases in VIX and EPU in at least one volatility regime in most of the cases, suggesting that rises in investor fear and economic policy uncertainty may induce a significant drop in REIT returns. This is consistent with Liow and Huang (2018) who find that VIX and EPU are among the most influential risk factors for REITs. Theoretically, uncertainties may negatively affect REIT returns because they are non-diversifiable; systematic risk cannot be diversified away and depresses asset prices by increasing the required rate of return. Pástor and Veronesi (2013) argue that uncertainties affect stock prices by influencing the amount of capital and causing investors to revise their beliefs about the impact of uncertainties. They further show that the risk premium is state-dependent, which partially supports our findings. The results are also in line with Philippas et al. (2013) who show that rises in VIX, as a measure of investor sentiment barometer, are negatively related to REIT returns, suggesting potential herding effects. In periods of heightened volatility, financial market participants tend to imitate each other's trading strategies, which in turn further accelerates price falls. We also observe positive coefficients only in the low volatility state; for example, SKEW and VIX exert statistically significant and positive effects on retail REITs, while the storage (timber) index is positively impacted by increases in EPU and PCI (only EPU). Therefore, some REIT sector returns significantly increase in periods of heightened uncertainty, indicating that they can be safe and still provide positive returns amidst volatile markets. This is somewhat in contrast with previous studies that report diminished diversification benefits of broad REITs in periods of high volatility (see, Chong et al., 2009; Heaney and Sriananthakumar, 2012; Abuzayed et al., 2020, among others). However, these studies analyse the investment benefits of REITs by only focusing on the aggregate REIT indices while ignoring sectoral differences. Thus, our results highlight that understanding the extent to which uncertainty factors affect REIT sectors can provide significant insights for investors and portfolio managers as broad REIT indices may not tell a complete story.

Moreover, our third research question seeks to answer which REIT sector is the most (least) vulnerable to various uncertainties. Overall, our empirical results show that uncertainty factors generate heterogeneous influences on REIT returns, as the magnitude and statistical significance of the responses to uncertainties vary across sectors. For example, judging by the magnitude of the coefficients, among all the others, office REITs exhibit the strongest sensitivity to VIX in the high volatility regime, which shows that investor pessimism and the resulting increase in the implied volatility cause a drop in office REIT returns, particularly when the market enters bear territory. In addition, hotel & lodging sector is the most vulnerable to economic policy uncertainty in the high variance state, suggesting that increasing number of newspaper references to uncertainty regarding economic policies leads to a fall in the sector's returns. On the other hand, the results from the MRS models show that residential REITs is the most resilient, with no significant exposure to any of the uncertainty factors. This is in line with Anderson et al. (2003) who argue that residential investments, particularly apartments, have a more predictable and stable demand base compared to other property types; hence, they are more efficient and less sensitive to sharp cyclical variations. They further claim that other property sectors, such as hotel & lodging and office, are more volatile, as their demand is more cyclical and closely linked to the overall economic performance. Newell and Fischer (2009) also assert that, especially after the subprime mortgage crisis in 2007, institutional investors have shown an increasing interest in residential REITs and have been more optimistic about the demand and supply side for apartments, compared to the other sectors. In a more recent study, Yunus (2017) shows that the residential sector is quite unique in the way that it has a profound impact on other REIT sectors, but it is not significantly affected from the others, suggesting that the residential sector is the dominant sector, which is highly exogenous, in the REITs universe. All these can make residential REITs less susceptible to uncertainties. Moreover, healthcare REIT returns are negatively and significantly affected from all the uncertainty factors, but only in the low volatility regime, which is consistent with Reddy and Cho (2018) who claim that healthcare REITs are typically recession resistant because of relatively inelastic demand for healthcare services.

The asymmetric impact of uncertainty measures on REIT sectors is also linked to notably differing return dynamics between real estate sectors. Many earlier studies suggest that the price dynamics of REIT sectors substantially vary (Wheaton, 1999; Yavas and Yildirim, 2011; Hoesli and Oikarinen, 2012). Furthermore, as stated in Brounen et al. (2000) and Jackson (2009), the return performance of individual REITs is related to the performance of the underlying asset, which in turn significantly impacts the sector in which the REIT belongs to. Boudry et al. (2012) also find that REITs and underlying real estate share long-run equilibrium. Therefore, any shock, such as demand and supply-side shocks or policy-related uncertainty, affecting the underlying asset also has an influence on the REIT subsector. For instance, consider hotel & lodging REITs which is found to be the most vulnerable REIT index to EPU in the high volatility regime. As suggested by Jackson (2009), hotel & lodging REITs are particularly sensitive to economic shocks; during the periods of economic downturns, hotel occupancy and room rates are much lower, this is because individuals tend to postpone or cancel their travel plans, resulting in lower earnings in hospitality and leisure sector. Depressed earnings in the industry translate into lower expected returns on hotel & lodging REITs. Some recent studies focusing on the impacts of the novel COVID-19 pandemic on REITs also highlight sector-specific reactions to uncertainties. For example, Akinsomi (2020) finds that some defensive REITs, such as self-storage or medical REITs, are less susceptible to the negative effects of the pandemic. In a more comprehensive study, Ling et al. (2020) conclude that retail REITs react more negatively to the increase in the number of COVID-19 cases while healthcare REITs are positively correlated with the COVID-19 cases. It is worth noting that even though our sample period covers the COVID-19 period, analysing the effects of the pandemic on REITs is beyond the scope of this paper. Nevertheless, sector-specific response to the COVID-19 outbreak found in recent empirical studies partially supports our findings of sectoral differences in terms of reaction to various uncertainty measures during different market conditions.

5 Conclusion and Implications

Even though a large body of empirical literature investigates the effects of various uncertainty measures on stock returns, the response of securitized real estate to different types of uncertainties is still an untouched subject. Most of the relevant papers analysing the relationship between risk factors and REITs focus on the impacts of the implied volatility (VIX) and ignore other forms of uncertainty, such as policy-induced economic uncertainty or political risk. The main contribution of this paper is to examine the impacts of different uncertainty measures (i.e., SKEW, VIX, EPU and PCI) on REIT returns at sector level in a regime-switching environment. As this is the first study that comprehensively investigates the effects of various forms of risk factors on REITs, we extend the findings of the existing literature that focuses on the relationship between uncertainty indicators and financial markets.

Our main findings can be summarized as follows: First, the effects of uncertainty measures are sector-specific, highlighting the importance of the use of sector-level data in REIT studies. Therefore, if we consider only aggregate REITs indices, instead of sub-sector REIT indices separately, then we are not able to offer a complete picture. Second, the return dynamics of REITs exhibit strong regime-switching characteristics, suggesting that linearity assumption may lead to a model misspecification. Third, the effects of uncertainty measures significantly vary across regimes; for example, hotel & lodging, speciality, and timber REITs tend to respond negatively to increases in EPU, only during bearish market episodes. Heightened political risk, proxied by rises in PCI, exerts significant negative effects on healthcare REITs but only in the low-variance state. Hence, our results provide evidence that uncertainty factors have asymmetric impacts on REIT returns. Fourth, VIX and EPU seem to be more useful in explaining REIT returns than SKEW and PCI as more than half of the REIT sectors hold strong sensitivity to VIX and EPU in at least one volatility regime.

Our results provide valuable insights and important implications for investors and portfolio managers. REIT investors should consider property types when making portfolio decisions, as our analysis shows considerable differences across REIT sub-sectors regarding their responses to uncertainties. Some REIT sectors are more vulnerable to uncertainties than others, thus investors should allocate their portfolios accordingly. Residential sub-sector is the only REIT sector not impacted by any of the risk factors, suggesting that residential REITs can offer significant diversification benefits in times of heightened uncertainty. Moreover, understanding how REITs respond to uncertainties across different regimes can provide useful information for traders and portfolio managers and help them formulate different trading strategies under changing market conditions.

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Table 1. Variable descriptions

Variables	Source	Explanation
REITs		
Healthcare	Datastream Eikon	This index lists companies that own, finance or operate income-generating healthcare-related property such as hospitals, medical office buildings and nursing homes.
Hotel & Lodging	Datastream Eikon	This index lists companies that acquire, own and manage hotels, motels, luxury resorts and other hospitality related properties.
Industrial	Datastream Eikon	This index lists companies that own, operate, and manage industrial facilities, such as distribution centres, manufacturing facilities and warehouses.
Office	Datastream Eikon	This index lists companies that own and manage office buildings and rent space in those properties to tenants.
Residential	Datastream Eikon	This index lists companies that own and operate rental properties, including apartment buildings, single-family homes and student housing.
Retail	Datastream Eikon	This index lists companies that own and manage retail properties such as shopping malls, outlet centres and grocery stores.
Speciality	Datastream Eikon	This index lists companies that own, acquire and operate a diverse set of properties that do not fit within the other REIT sectors, such as gaming properties, movie theatres and casinos.
Self Storage	Datastream Eikon	This index lists companies that own, acquire and manage self-storage facilities like outside storage, indoor storage and climate-controlled storage.
Timber	Datastream Eikon	This index lists companies that own, acquire and operate land used for the production and harvesting of timber.
Aggregate REIT	Datastream Eikon	This is a free float-adjusted market capitalization weighted index that is comprised of equity REITs.
Asset pricing factors		
Market risk premium	K. French's website	It is calculated as the difference between the expected return on the market portfolio and the one-month T-bill rate.
Small minus Big	K. French's website	It is one of Fama and French (1992)'s factors which reflects the size effect and measures the historic excess of small companies over big companies in terms of market capitalization.
High minus Low	K. French's website	It is one of Fama and French (1992)'s factors which reflects the value premium and accounts for the spread in returns between value and growth companies.
Momentum	K. French's website	It is an extra factor added by Carhart (1997) to Fama and French (1992)'s three-factor model and computed as average return on high prior return portfolios minus the average return on low prior return portfolios.

Macroeconomic variables		
Industrial production	FRED	This index represents real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities.
Inflation	FRED	The Consumer Price Index for All Urban Consumers All Items (CPIAUCSL) is used as a measure of the average monthly change in the price for goods and services.
Unemployment	FRED	The unemployment rate is measured as the number of unemployed as a percentage of the labour force.
Credit spread	FRED	It is computed as the difference between Moody's seasoned Baa corporate bond and 10-year Treasury constant maturity.
Term spread	FRED	It is calculated as the difference between 10-year Treasury constant maturity rate and one-year Treasury constant maturity rate.
Uncertainty measures		
Economic Policy Uncertainty (EPU)	Baker's website	EPU is a news-based economic policy uncertainty index constructed based on newspaper archives.
Partisan Conflict (PCI)	FRBP	PCI is designed to track the degree of political disagreement among U.S. politicians at the federal level.
SKEW	Yahoo finance	SKEW index measures the perceived tail risk of the return distribution of S&P 500 index over a 30-day horizon.
VIX	Yahoo finance	It is a measure of the stock market's expectation of volatility based on S&P 500 index options over a 30-day horizon.

Notes: This table illustrates the research variables, their explanations and sources. FRED refers to St Louis' Federal Reserve Economic Database website. FRBP represents Federal Reserve Bank of Philadelphia.

Table 2. Summary statistics of REIT returns

	HEALTH	HOTEL	INDUST.	OFFICE	RESIDENT.	RETAIL	SPECIALITY	STORAGE	TIMBER	REITs
Mean	0.462	0.194	0.514	0.557	0.582	0.284	0.670	0.793	0.257	0.453
Median	1.143	1.004	1.274	1.517	1.291	1.204	1.295	1.088	1.051	1.247
Maximum	36.341	55.074	21.403	19.788	22.594	27.319	27.342	22.323	23.282	21.186
Minimum	-83.117	-104.343	-49.456	-50.019	-42.111	-81.612	-29.363	-26.568	-61.709	-42.604
Std. Dev.	7.854	11.461	6.689	7.420	6.139	7.704	5.960	6.234	8.985	6.056
Skewness	-3.565	-2.292	-2.024	-2.339	-1.991	-4.298	-0.799	-0.507	-1.338	-2.281
Kurtosis	38.873	25.500	16.508	17.215	15.013	42.801	8.336	5.305	9.686	17.653

Table 3. BDS test results

		HEALTH	HOTEL	INDUST.	OFFICE	RESIDENT.	RETAIL	SPECIALITY	STORAGE	TIMBER	REITs
ε(0.5)	m=2	0.003	0.021 [a]	0.010 [a]	0.018 [a]	0.007 [a]	0.009 [b]	0.006 [b]	0.001	0.001	0.009 [a]
		(0.284)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.018)	(0.360)	(0.464)	(0.003)
	m=3	0.003	0.021 [a]	0.010 [a]	0.018 [a]	0.007 [a]	0.013 [a]	0.008 [a]	0.001	0.003 [c]	0.012 [a]
		(0.189)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.202)	(0.090)	(0.002)
ε(0.75)	m=2	0.008[c]	0.033 [a]	0.014 [a]	0.028 [a]	0.013 [a]	0.017 [a]	0.011 [a]	0.003	0.002	0.016 [a]
		(0.050)	(0.000)	(0.004)	(0.000)	(0.002)	(0.000)	(0.007)	(0.236)	(0.494)	(0.000)
	m=3	0.012[b]	0.044 [a]	0.022 [a]	0.038 [a]	0.017 [a]	0.030 [a]	0.019 [a]	0.004	0.008 [b]	0.028 [a]
		(0.034)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.160)	(0.036)	(0.000)
ε(1)	m=2	0.010[b]	0.038 [a]	0.017 [a]	0.033 [a]	0.019 [a]	0.020 [a]	0.014 [a]	0.004	0.004	0.019 [a]
		(0.041)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.249)	(0.349)	(0.000)
	m=3	0.019[b]	0.063 [a]	0.031 [a]	0.057 [a]	0.029 [a]	0.041 [a]	0.028 [a]	0.007	0.014 [b]	0.039 [a]
		(0.018)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.162)	(0.010)	(0.000)
ε(1.5)	m=2	0.012[a]	0.031 [a]	0.019 [a]	0.031 [a]	0.025 [a]	0.016 [a]	0.016 [a]	0.008 [c]	0.004	0.018 [a]
		(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.057)	(0.265)	(0.000)
	m=3	0.025[a]	0.063 [a]	0.042 [a]	0.066 [a]	0.048 [a]	0.040 [a]	0.035 [a]	0.016 [b]	0.019 [b]	0.044 [a]
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.010)	(0.000)

Notes: Bootstrap *p*-values are given in the parentheses. a, b, c represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4. Linear model results

	HEALTH	HOTEL	INDUST.	OFFICE	RESIDENT.	RETAIL	SPECIALITY	STORAGE	TIMBER	REITs
α	3.520	2.123	-7.429	0.767	1.288	-0.830	3.298	2.804	-6.009	0.868
	(6.517)	(8.435)	(5.246)	(5.790)	(4.952)	(5.815)	(4.773)	(5.411)	(6.759)	(4.602)
MARKET PREMIUM	0.405[a]	0.622[a]	0.364[a]	0.299[a]	0.328[a]	0.450[a]	0.290[a]	0.303[a]	0.887[a]	0.347[a]
	(0.104)	(0.135)	(0.084)	(0.092)	(0.079)	(0.093)	(0.076)	(0.086)	(0.108)	(0.073)
SMB	0.287[b]	0.736[a]	0.370[a]	0.332[a]	0.346[a]	0.434[a]	0.371[a]	0.297[a]	0.231[c]	0.371[a]
	(0.128)	(0.166)	(0.103)	(0.114)	(0.097)	(0.114)	(0.094)	(0.106)	(0.133)	(0.091)
HML	0.430[a]	0.801[a]	0.520[a]	0.547[a]	0.488[a]	0.607[a]	0.277[a]	0.378[a]	0.791[a]	0.442[a]
	(0.130)	(0.169)	(0.105)	(0.116)	(0.099)	(0.116)	(0.096)	(0.108)	(0.135)	(0.092)
MOMENTUM	-0.217[b]	-0.368[a]	-0.153[b]	-0.192[b]	-0.106	-0.215[a]	-0.222[a]	-0.095	-0.180[b]	-0.167[a]
	(0.085)	(0.111)	(0.069)	(0.076)	(0.065)	(0.076)	(0.063)	(0.071)	(0.089)	(0.060)
IND. PRODUCTION	0.188	-0.699	-0.538	0.525	0.031	0.245	-0.560	-0.449	0.173	-0.229
	(0.548)	(0.710)	(0.441)	(0.487)	(0.417)	(0.489)	(0.402)	(0.455)	(0.569)	(0.387)
INFLATION	1.578	-3.216	1.118	1.615	0.031	0.063	-1.056	-1.632	-0.148	-0.418
	(1.520)	(1.968)	(1.224)	(1.351)	(1.155)	(1.357)	(1.113)	(1.262)	(1.577)	(1.073)
UNEMPLOYMENT	0.190[b]	-0.025	0.022	0.134[c]	0.080	0.016	0.006	-0.071	0.022	0.038
	(0.079)	(0.103)	(0.064)	(0.070)	(0.060)	(0.071)	(0.058)	(0.066)	(0.082)	(0.056)
CREDIT SPREAD	-0.106	-0.343[a]	-0.153[a]	-0.177[a]	-0.059	-0.190[a]	-0.064	0.055	-0.221[a]	-0.126[a]
	(0.065)	(0.084)	(0.053)	(0.058)	(0.050)	(0.058)	(0.048)	(0.054)	(0.068)	(0.046)
TERM SPREAD	0.044	0.197	-0.160	0.053	0.036	0.125	0.115	0.351	-0.135	0.012
	(0.368)	(0.476)	(0.296)	(0.327)	(0.279)	(0.328)	(0.269)	(0.305)	(0.381)	(0.260)
SKEW	-0.011	0.051	0.093[b]	0.031	0.015	0.044	0.012	0.008	0.051	0.030
	(0.057)	(0.074)	(0.046)	(0.051)	(0.043)	(0.051)	(0.042)	(0.047)	(0.059)	(0.040)
VIX	-0.102	-0.183[b]	-0.095[c]	-0.147[b]	-0.105[b]	-0.101	-0.152[a]	-0.110[b]	0.019	-0.127[a]
	(0.069)	(0.089)	(0.055)	(0.061)	(0.052)	(0.061)	(0.050)	(0.057)	(0.071)	(0.049)
EPU	-0.004	-0.021[b]	-0.001	-0.011	-0.008	-0.012[c]	0.002	-0.001	-0.002	-0.005
	(0.008)	(0.010)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.006)
PCI	0.001	-0.015	-0.011	-0.003	-0.002	-0.010	-0.012	-0.009	-0.002	-0.009
	(0.013)	(0.017)	(0.011)	(0.012)	(0.010)	(0.012)	(0.010)	(0.011)	(0.014)	(0.009)
R^2 (%)	23.4	39.8	31.6	32.3	27.7	36.7	28.7	16.2	37.1	35.8

Notes: a, b, c represent statistical significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are given in the parentheses.

Table 5. Non-linear Markov regime-switching results

	HEALTH	HOTEL	INDUST.	OFFICE	RESIDENT.	RETAIL	SPECIALITY	STORAGE	TIMBER	REITs
Panel A. Low Volatility										
Constant	41.240[a]	1.451	-7.849	-2.302	5.657	-37.152[a]	7.173[c]	37.280[a]	-3.408	4.783
	(4.236)	(5.986)	(5.943)	(4.713)	(4.724)	(8.368)	(4.360)	(5.078)	(9.840)	(3.745)
MARKET PREMIUM	-0.545[a]	0.353[a]	0.429[a]	0.346[a]	0.033	1.956[a]	0.194[a]	0.154[b]	0.445[a]	0.249[a]
	(0.045)	(0.112)	(0.100)	(0.087)	(0.087)	(0.144)	(0.070)	(0.071)	(0.170)	(0.073)
SMB	1.627[a]	0.480[a]	0.393[a]	0.176[c]	0.272[a]	1.518[a]	0.272[a]	0.459[a]	0.868[a]	0.456[a]
	(0.072)	(0.117)	(0.129)	(0.094)	(0.096)	(0.270)	(0.090)	(0.074)	(0.218)	(0.090)
HML	-0.701[a]	0.511[a]	0.293[b]	0.298[a]	-0.034	0.846[a]	0.234[b]	0.849[a]	0.425[c]	0.328[a]
	(0.060)	(0.138)	(0.124)	(0.098)	(0.110)	(0.144)	(0.091)	(0.079)	(0.226)	(0.086)
MOMENTUM	-1.692[a]	-0.172[b]	-0.086	-0.051	-0.166[b]	0.134[c]	-0.159[a]	-0.210[a]	0.228[c]	-0.017
	(0.080)	(0.0860	(0.087)	(0.066)	(0.070)	(0.075)	(0.054)	(0.053)	(0.137)	(0.059)
IND. PRODUCTION	4.491[a]	0.000	0.093	-0.338	-0.309	3.854[a]	-0.953[b]	-2.482[a]	-0.029	-0.095
	(0.290)	(0.593)	(0.426)	(0.430)	(0.411)	(0.579)	(0.418)	(0.308)	(0.666)	(0.421)
INFLATION	0.377	-2.973[c]	-5.575[a]	-2.996[b]	-3.533[a]	6.517[a]	-2.679[b]	2.010[b]	0.539	-2.475[b]
	(0.547)	(1.636)	(1.381)	(1.231)	(1.196)	(1.228)	(1.088)	(0.907)	(2.279)	(1.040)
UNEMPLOYMENT	-0.959[a]	-0.212[c]	0.023	0.059	0.066	0.525[a]	0.012	-0.639[a]	0.032	0.028
	(0.092)	(0.110)	(0.057)	(0.058)	(0.054)	(0.082)	(0.080)	(0.086)	(0.093)	(0.073)
CREDIT SPREAD	0.133[a]	-0.072	0.080	-0.061	0.167[a]	-0.139[b]	0.028	-0.058	-0.039	0.063
	(0.035)	(0.069)	(0.074)	(0.057)	(0.056)	(0.055)	(0.046)	(0.039)	(0.103)	(0.050)
TERM SPREAD	8.178[a]	0.480	0.403	0.002	0.128	-2.237[a]	0.321	-0.967[a]	0.041	0.055
	(0.200)	(0.329)	(0.355)	(0.2640	(0.261)	(0.491)	(0.228)	(0.278)	(0.656)	(0.215)
SKEW	-0.287[a]	0.019	0.047	0.035	-0.004	0.351[a]	-0.040	-0.313[a]	0.021	-0.014
	(0.034)	(0.053)	(0.052)	(0.0420	(0.041)	(0.076)	(0.038)	(0.044)	(0.090)	(0.033)
VIX	-0.465[a]	-0.089	0.140	0.046	-0.090	0.336[a]	-0.101[b]	-0.229[a]	0.102	-0.118[b]
	(0.031)	(0.076)	(0.066)	(0.060)	(0.056)	(0.070)	(0.048)	(0.044)	(0.104)	(0.049)
EPU	-0.033[a]	-0.002	0.009	-0.015[c]	-0.004	-0.096[a]	0.003	0.037[a]	0.021[c]	0.003
	(0.005)	(0.008)	(0.008)	(0.008)	(0.006)	(0.011)	(0.007)	(0.006)	(0.013)	(0.006)
PCI	-0.128[a]	-0.015	0.003	0.003	-0.009	-0.006	0.001	0.016[c]	-0.025	-0.003
	(0.009)	(0.013)	(0.012)	(0.011)	(0.010)	(0.015)	(0.010)	(0.009)	(0.022)	(0.008)
Sigma	0.634[a]	1.673[a]	2.669[a]	1.435[a]	3.781[a]	1.718[a]	2.865[a]	1.733[a]	4.888[a]	1.117[a]
	(0.149)	(0.051)	(0.231)	(0.049)	(0.199)	(0.294)	(0.237)	(0.230)	(0.416)	(0.062)

Panel B. High Volatility										
Constant	3.494	-20.735	-7.942	31.581	-18.740	4.446	-2.001	-10.117	-2.918	-19.679
	(4.637)	(66.579)	(12.340)	(30.240)	(20.640	(4.286)	(32.573)	(7.167)	(11.820)	(18.896)
MARKET PREMIUM	0.199[b]	0.418	0.331[b]	-0.767[c]	1.122[a]	0.075	0.636[b]	0.286[b]	0.909[a]	0.373[c]
	(0.076)	(0.575)	(0.147)	(0.415)	(0.194)	(0.069)	(0.315)	(0.118)	(0.182)	(0.207)
SMB	0.193[c]	1.147	0.126	0.162	0.586[b]	0.178[b]	2.056[a]	0.217	-0.196[a]	0.222
	(0.101)	(0.946)	(0.183)	(0.641)	(0.246)	(0.084)	(0.673)	(0.150)	(0.213)	(0.255)
HML	0.045	0.516	0.497[b]	0.237	1.441[a]	0.103	-0.436	0.164	0.462[b]	0.352
	(0.097)	(0.698)	(0.203)	(0.865)	(0.230)	(0.089)	(0.490)	(0.149)	(0.223)	(0.297)
MOMENTUM	-0.160[b]	-0.666	-0.052	-1.032[b]	0.023	-0.134[b]	0.005	-0.005	-0.455[a]	-0.418[b]
	(0.062)	(0.535)	(0.148)	(0.467)	(0.124)	(0.059)	(0.389)	(0.100)	(0.127)	(0.173)
IND. PRODUCTION	-0.938[b]	-6.414[b]	-0.706	2.606	0.408	-0.897[b]	0.425	0.285	1.284	-0.934
	(0.422)	(2.957)	(0.937)	(3.110)	(1.061)	(0.375)	(1.378)	(0.628)	(1.040)	(0.984)
INFLATION	-2.369[b]	-5.215	3.863[b]	7.718	3.307	-5.117[a]	-0.421	-5.981[a]	-0.826	2.144
	(1.164)	(6.793)	(1.844)	(5.198)	(2.366)	(1.136)	(4.055)	(1.744)	(2.293)	(2.825)
UNEMPLOYMENT	0.131[c]	-0.248	0.119	-0.353	0.112	-0.047	0.106	0.003	-0.370[c]	-0.010
	(0.057)	(0.358)	(0.178)	(0.684)	(0.152)	(0.053)	(0.157)	(0.084)	(0.196)	(0.132)
CREDIT SPREAD	0.118[b]	-0.371	-0.299[a]	0.022	-0.095	0.012	-0.117	0.243[a]	-0.264[a]	-0.255[b]
	(0.054)	(0.325)	(0.099)	(0.201)	(0.104)	(0.046)	(0.148)	(0.081)	(0.098)	(0.112)
TERM SPREAD	0.009	1.977	-0.556	3.817	1.012	0.549[b]	-6.582[c]	0.982[b]	0.033	0.017
	(0.262)	(4.230)	(0.546)	(2.334)	(0.876)	(0.243)	(3.535)	(0.410)	(0.667)	(0.929)
SKEW	-0.015	0.327	0.183	-0.119	0.130	0.007	0.292	0.128	0.024	0.232
	(0.041)	(0.558)	(0.112)	(0.271)	(0.174)	(0.037)	(0.246)	(0.064)	(0.108)	(0.169)
VIX	-0.015	-0.469	-0.416[a]	-0.943[b]	-0.017	-0.095[b]	0.029	-0.006	-0.025	-0.091
	(0.052)	(0.345)	(0.104)	(0.406)	(0.123)	(0.048)	(0.181)	(0.076)	(0.114)	(0.146)
EPU	0.004	-0.140[b]	-0.004	0.008	0.004	-0.003	-0.080[a]	-0.010	-0.026[b]	-0.023
	(0.006)	(0.060)	(0.009)	(0.032)	(0.020)	(0.005)	(0.022)	(0.009)	(0.012)	(0.015)
PCI	-0.002	0.087	-0.055[b]	-0.049	-0.015	-0.017[c]	-0.108[b]	-0.030[b]	0.013	-0.031
	(0.010)	(0.129)	(0.021)	(0.066)	(0.030)	(0.009)	(0.047)	(0.015)	(0.022)	(0.031)
Sigma	4.712[a]	2.702[a]	5.098[a]	4.812[a]	4.026[a]	3.817[a]	5.391[a]	5.788[a]	6.913[a]	3.952[a]
	(0.188)	(0.115)	(0.375)	(0.183)	(0.597)	(0.156)	(0.383)	(0.271)	(0.429)	(0.090)

Notes: a, b, c represent statistical significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are given in the parentheses.

Table 6. Descriptive statistics for the regime-switching models

	HEALTH	HOTEL	INDUST.	OFFICE	RESIDENT.	RETAIL	SPECIALITY	STORAGE	TIMBER	REITs
$duration_{low}$	1.040	30.920	41.152	14.639	11.520	1.260	39.586	43.462	5.662	28.023
$duration_{high}$	14.380	5.627	22.104	2.131	1.250	9.165	5.156	2.656	1.306	9.579
p_{11}	0.045	0.968	0.976	0.932	0.815	0.206	0.975	0.977	0.823	0.964
p_{21}	0.955	0.032	0.024	0.068	0.185	0.794	0.025	0.023	0.177	0.036
p_{12}	0.081	0.178	0.045	0.469	0.720	0.109	0.194	0.376	0.766	0.104
p_{22}	0.919	0.822	0.955	0.531	0.280	0.891	0.806	0.624	0.234	0.896
RCM	8.421	15.893	21.119	22.708	43.700	22.414	9.651	2.508	35.115	24.082

Notes: $duration_{low}$ and $duration_{high}$ represent expected duration (in months) in the low and high volatility regime, respectively. P_{km} denotes the estimated transitional probabilities. RCM stands for the Regime Classification Measure of Ang and Bekaert (2002).

Table 7. Tests for coefficient equality between low and high variance regimes for uncertainty measures estimates

	HEALTH	HOTEL	INDUST.	OFFICE	RESIDENT.	RETAIL	SPECIALITY	STORAGE	TIMBER	REITs
SKEW	25.771[a]	0.298	0.930	0.305	0.508	16.317[a]	1.762	28.157[a]	0.000	1.960
	(0.000)	(0.585)	(0.335)	(0.581)	(0.476)	(0.000)	(0.184)	(0.000)	(0.988)	(0.162)
VIX	56.349[a]	1.136	17.730[a]	5.682[b]	0.250	22.833[a]	4.476[b]	5.807[b]	0.515	4.277[b]
	(0.000)	(0.287)	(0.000)	(0.017)	(0.617)	(0.000)	(0.049)	(0.016)	(0.473)	(0.039)
EPU	23.899[a]	5.110[b]	0.983	0.448	0.148	55.607[a]	12.436[a]	18.315[a]	6.449[b]	2.648
	(0.000)	(0.024)	(0.322)	(0.504)	(0.700)	(0.000)	(0.000)	(0.000)	(0.011)	(0.104)
PCI	94.180[a]	0.594	4.612[b]	0.579	0.040	0.407	4.957[b]	6.180[b]	1.134	0.701
	(0.000)	(0.441)	(0.032)	(0.447)	(0.841)	(0.523)	(0.026)	(0.013)	(0.287)	(0.402)

Notes: a, b, c represent statistical significance at the 1%, 5% and 10% levels, respectively. *p*-values are given in the parentheses.

Figure 1. Time evolution of uncertainty measures

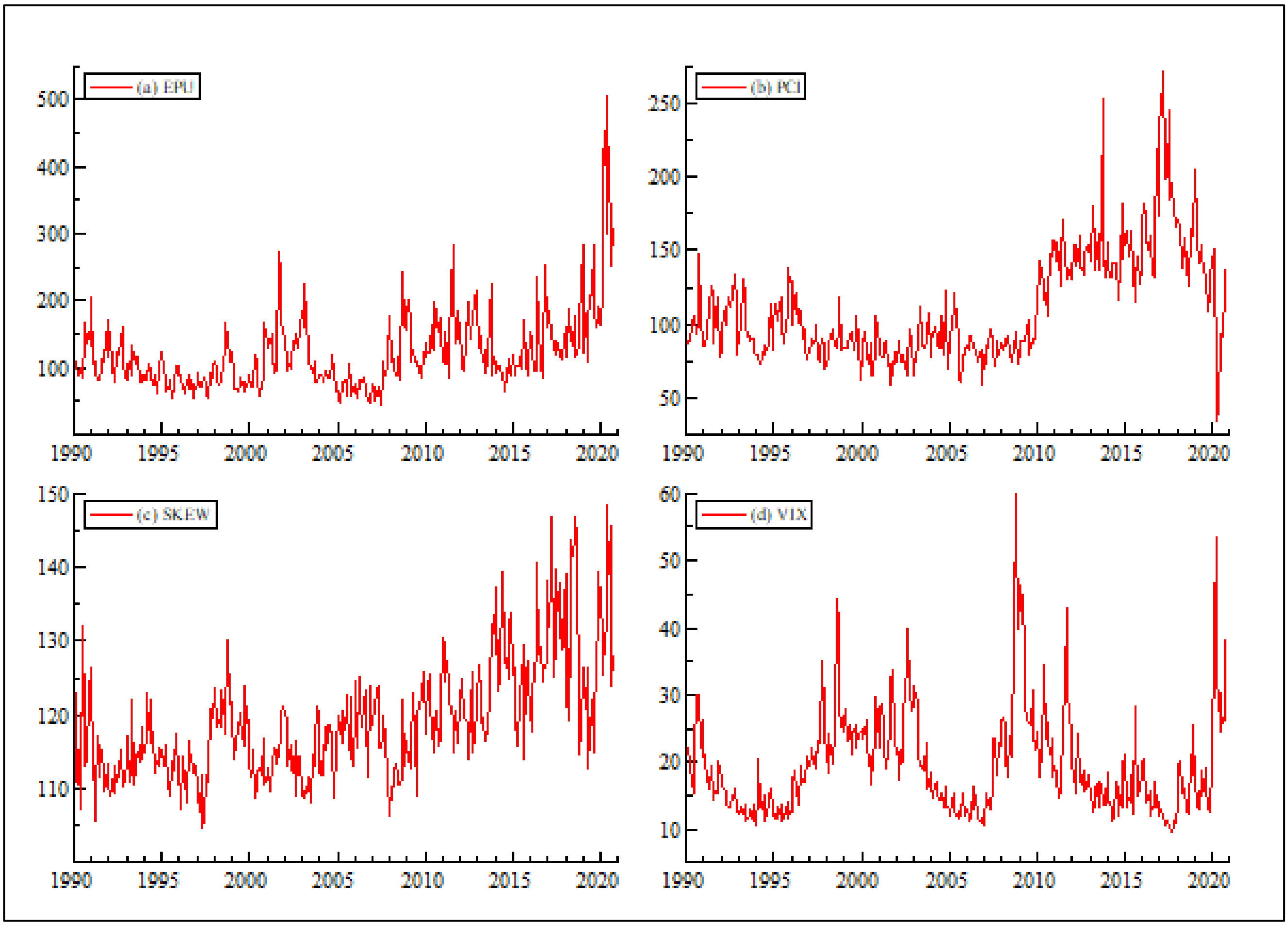

Figure 2. Smoothed probability of high volatility state (blue line) and return series (red line)