THE ROLE OF REIT DIVIDEND POLICY ON EX-ANTE PORTFOLIO ALLOCATION

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ABSTRACT

To test the diversification benefits of REIT sub-groups formed based on dividend payout ratios, we forecast ex-ante variance-covariance matrices using a rolling window correlation and a DCC model. Regression-based mean-variance spanning tests, mean-variance efficient frontiers, and a minimum variance portfolio allocation approach using ex-ante optimization frameworks are considered. A major finding of the current study is the dividend payout ratios of REITs affect REIT market diversification benefits. Apart from extending stock market index investors' investment universe and providing more efficient (higher profitability and/or lower risk) portfolios, REITs offer diversification benefits directly related to dividend policies. A unique level of diversification is attained by classifying REITs based on their dividend payout ratios. As well, these REIT sub-groups are capable of left-shifting the efficient frontier of a market portfolio with either of the REIT sub-groups.

KEY WORDS

DCC, REITs, correlation, dividend policy, portfolio optimization, estimation, forecasting

JEL CODES

G14, G18, G32, H12

1 INTRODUCTION

The real estate market has proven to be an asset class with high diversification potential for the stock market investors (Lu et al., 2013; Yang et al., 2012; Case et al., 2012; Fugazza et al., 2007; Clayton and MacKinnon, 2001; Bley and Olson, 2005; Cotter and Stevenson, 2006; Chong et al., 2009; Liow et al., 2009; Niskanen and Falkenbach, 2010; Akinlana et al., 2019). A specific area of literature examines whether diversification benefits of real estate to equity market investors are related real estate investment trusts' (REITs) dividend policies

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(Allen and Rachim, 1996; Hussainey et al., 2011; İlbasmış et al., 2025). For example, İlbasmış et al. (2025) report that the REIT dividend payout ratio is negatively correlated with the time-varying correlation when REITs face restrictions on their dividend payout policies. This suggests that the REIT dividend policy has the potential to reduce REITs' correlation with the stock market. The modern portfolio theory posits that it means that the diversification benefits assigned to each asset class are different if two asset classes have different levels of correlation with the general stock market.

Whilst the literature on mixed-asset portfolios including REIT has demonstrated the contribution of REIT in enhancing portfolio performance, most studies rely on ex-post and in-sample results. In the absence of a solid grounding in asset pricing theory, portfolio allocations using ex-post models with in-sample data may be unrealistic for active portfolio managers in real world scenarios. For a more convincing portfolio allocation practice, we use an out-of-sample portfolio allocation with ex-ante variance-covariance matrix forecasts. Taking the stock market index portfolio as an optimal portfolio that comprises the efficient frontier, we investigate whether portfolios including REITs with different dividend payout policies in this portfolio further expands the investment opportunity set and improves the efficient frontier differently.

This study aims to document the differential diversification power of REIT sub-groups formed based on their dividend payout ratios and to test the extent to which they can diversify a stock market portfolio. Thus, our attention focuses on the differences in the efficient frontier obtained when a different sub-group of REITs is added to the stock market portfolio.

Companies that own or finance income-producing real estate across a variety of property sectors are known as REITs. They are required to distribute a considerable share of their earnings as dividends in order to keep their REIT status and continue to enjoy the tax advantages provided by governments around the world. For instance, according to the Securities and Exchange Commission (SEC), "To qualify as a REIT, a company must have the bulk of its assets and income connected to real estate investment and must distribute at least 90 percent of its taxable income to shareholders annually in the form of dividends.[1]" Any non-distributed income over the threshold is taxed at the corporate level of 35%.

Our sample comprises weekly returns on the stock market index and REITs spanning from January 2000 to December 2022, covering two significant global economic crises: the 2008 Global Financial Crisis and the recent Covid-19 pandemic crisis. After creating groups of REITs with high- and low-dividend-payments, we first use a mean- variance spanning test to examine whether these sub-groups of REITs can lead to a statistically significant improvement in the efficient frontier. Second, to assess the economic significance of these improvements, we optimize global minimum variance portfolios consisting of the stock market index and a sub-group of REITs using both ex-post and ex-ante covariance matrices. In doing so, we use two forecasting models, the Dynamic Conditional Correlation (DCC) and rolling window correlation (RWC), to acquire the covariance matrix.

Various contributions have been made to the literature on REITs' dividend policy and diversification power. We first document that the efficient frontier of the market portfolio is influenced by the dividend policies of REITs in the portfolio. In other words, as well as expanding investment opportunities for stock market index investors and providing more profitable or less risky portfolios, REIT dividend policies contribute directly to their diversification benefits. Investing in REITs that are categorized based on dividend payout ratios offers varying levels of diversification. To our knowledge, this study is the first to document improvements in the efficient frontier of the market portfolio due to differential dividend policies. Second, our study contributes to the forecasting literature by using a DCC and a rolling window correlation model in ex-ante

[1] The minimum dividend requirement was 95% prior to 2001.

portfolio allocation. Each model employed in this study has its own advantages and disadvantages. For instance, although both models produce similar levels of expected returns for a portfolio of the stock market index and a REIT sub-group, the DCC model out-performs the rolling window correlation model in mitigating the risk of the portfolio. What is more, the rolling window correlation model produces portfolios with better risk-return combinations, while the DCC model allows investors to form portfolios with higher risk and higher return. These outcomes hold both at the index level and the firm level portfolio allocation.

Several interesting findings come out of this study. First, we find that the two sub-groups of REITs formed based on the dividend payout ratio cannot be spanned by a market portfolio consisting of the stock market index. Furthermore, the sub-groups are not a substitute for each other in portfolio allocation. Analyses are conducted at both index and firm levels and our findings are confirmed with multiple methods, including Huberman and Kandel (1987)'s spanning test, and global minimum variance portfolio expected returns and standard deviations. The main finding is that REITs, when divided into sub-groups, continue to offer diversification opportunities to stock market investors, regardless of their investment in other REIT sub-groups. This implies that REITs provide diversification benefits both within and across asset allocations. Our sub-period analysis further reveals that the diversification potential of REITs and their sub-groups evolves over time. Notably, the diversification benefits of REITs were prominent before and during the 2008 global financial crisis. However, while REIT sub-groups still offer diversification benefits to stock market index investors post-crisis, their ability to diversify among different REIT sub-groups significantly diminishes. Additionally, our investigation of REITs' diversification power during the recent Covid-19 pandemic shows that REITs continue to offer diversification benefits to stock market investors.

The rest of the paper is organized as follows. Section 2 provides a brief overview of the relevant literature. Section 3 describes the data and outlines the mean-variance spanning test and the methodologies used to predict the correlation forecasts along with the global minimum variance problem. Section 4 presents the results from the spanning test, portfolio allocations, and time varying diversification benefits of subgrouped REITs. Finally, section 5 offers some concluding remarks and discusses our overall findings.

2 LITERATURE REVIEW

Owing to the low correlations of real estate with traditional asset classes, the literature has documented ample evidence on the diversification benefits of the real estate market in mixed-asset portfolios. Thus, after providing the literature on the overall role of the real estate market, this section focuses on the role of different real estate categories in mixed-asset portfolios.

Hudson-Wilson et al. (2003, 2005) addressed the question of "Why Real Estate?" providing central explanations for the inclusion of real estate in a mixed-asset portfolio. The authors rationalize that investors benefit by adding real estate to their portfolios in the following ways: i) reduction in risk or enlargement of returns, ii) hedging against inflation, iii) stable and high cash flows, and iv) expansion of the investment universe. Addressing a similar question, Garay and ter Horst (2009) review the literature on the diversification benefits of real estate investments and find that the real estate market improves mean-variance efficiency.

One of the early studies examining the diversification of the stock market via securitized real estate is Burns and Epley (1982). Using quarterly data from 1970 to 1979, they compared the location of the efficient frontier of portfolios consisting of REITs only, stocks only, and both. The combined portfolio of REITs and stocks was found to be superior to both single-asset portfolios. Thus, the authors conclude that the inclusion of REITs in the stock market portfolio improves risk-return opportunities for investors. On the other hand, a study by Mull and Soenen (1997) shows conflicting evidence that the diversification potential of REITs is dependent on the time period under examination. They report that the diversification potential of REITs were not attractive in the 1985–1990 period, while the 1990–1994 period was a good period to invest in REITs. Both of these papers study the ex-post diversification benefits of REITs.

Building on these foundational studies, more recent research has expanded the examination of REIT diversification benefits beyond the U.S. context. For instance, Badji et al. (2021) extended the analysis to European markets, showing that European REITs contribute to diversification in mixed portfolios, even if the risk reduction is limited. Similarly, Marzuki and Newell (2021) highlighted the significance of Mexico REITs, particularly in emerging markets, where they demonstrated strong risk-adjusted performance and diversification potential despite higher volatility.

Fugazza et al. (2007) used Bayesian estimators to account for parameter uncertainty when including U.S. REITs in optimal portfolios of stocks, bonds, and cash. Their findings indicate that ex-post gains from portfolios containing REITs are large, despite higher realized portfolio volatility. This work laid the foundation for understanding the significant ex-post benefits of including REITs in portfolios, even when considering the added volatility.

Sa-Aadu et al. (2010) addressed how real estate helps investors of stocks and bonds improve the performance of their portfolios using monthly data from January 1972 to December 2008. They investigate whether adding REITs to the portfolio in a regime-switching economy (the good times and the bad times) would decrease the lower bound of volatility, equivalent to increasing the Sharpe ratio of the portfolio. Their results indicate that gains from the inclusion of equity REITs lead to a considerable increase in portfolio performance across different economic states.

Further, Lin et al. (2020) focused on Industrial and Logistics REITs (I&L REITs) in the Pacific Rim region, examining their performance against other asset classes in mixed-asset portfolios. Their study revealed that I&L REITs offered superior average annual returns and provided significant portfolio diversification benefits. This is particularly relevant in the context of the growing importance of logistics properties driven by the e-commerce boom. Their findings underscore the added value of sector-specific REITs in enhancing portfolio performance, especially in regions heavily influenced by modern economic trends.

Huang and Zhong (2013), an important paper in this line of literature, examined in-sample and out-of-sample diversification opportunities by including REITs, commodities, and Treasury Inflation-Protected Securities (TIPS) into portfolios of U.S. equity, U.S. bonds, international equity, and international bonds. The study's sample period from 1970 to 2010 showed that none of these asset classes could substitute each other before the 2008 global financial crisis, although all had diversification potential. However, the 2008 crisis significantly altered their diversification roles, showing how economic crises can impact the effectiveness of REITs and other assets in a portfolio.

Additionally, Pacholec (2022) revisited the diversification potential of REITs by examining the impact of individual REIT sectors on mixed portfolios. His findings contrast earlier studies by showing that certain REIT sectors, such as Apartments and Industrials, consistently provided diversification benefits across different decades. His study demonstrated that replacing even small portions of traditional assets with sector-specific REITs could significantly enhance portfolio performance, particularly during specific market conditions.

Another area of literature examines the diversification benefits within real estate sub-classes. Hudson-Wilson and Elbaum (1995) conducted an early study on asset allocation within real estate, providing evidence for the diversification benefits of including public equity, public debt, and private debt securities in a real estate portfolio dominated by private equity. Their findings suggest that a diversified real estate portfolio can offer significant risk reduction and return enhancement by combining different types of real estate securities.

Building on this, Seiler et al. (1999) focused on the diversification potential of real estate in a mean-variance context. They reviewed literature concerning the optimal allocation of real estate within both real estate-only portfolios and mixed-asset portfolios that include real estate. Seiler et al. (1999) highlighted the varying approaches in the literature regarding the appropriate amount of real estate to include in a diversified portfolio. Their key conclusion was that while real estate significantly expands the investment universe, effective diversification often requires investing in different types of real estate, given the variations in property type, geographic location, and economic conditions. Importantly, they distinguished between unsecuritized and securitized real estate: unsecuritized real estate tends to have low correlations with other asset classes, making it a strong hedge against inflation, while securitized real estate (such as REITs) exhibits higher correlations with other asset classes, reducing its effectiveness as an inflation hedge.

Taking a different approach, Boudry et al. (2020) used a utility-based framework to assess the diversification benefits of REIT preferred and common stocks. Their findings emphasized that while REIT common stocks are beneficial for low-risk aversion investors seeking higher returns, REIT preferred stocks provide a venue for risk reduction. This distinction is crucial as it highlights the varying roles that different types of REIT securities can play in portfolio optimization.

Chen et al. (2005) investigated the characteristics of REITs that play a role in the diversification benefits. Their empirical results demonstrate that REITs did not provide diversification benefits prior to 1985. However, from 1986 to 2002, adding REITs to a portfolio did offer diversification benefits. In particular, mortgage REITs were found not to provide meaningful diversification, whereas equity REITs did. This study aligns with the broader literature that differentiates between the diversification potential of different REIT subtypes.

Further, recent research by Ervin and Smolira (2023) extends the discussion to the role of REITs in retirement portfolios. Their Monte Carlo simulations show that portfolios including REITs are more likely to sustain withdrawals over time, which is crucial for retirement planning. Lastly, Li et al. (2023) investigated the relationship between sector-specific Australian REITs and their underlying property assets, finding that property features like occupancy rates and portfolio market value significantly influence REIT dividend outcomes.

The real estate literature has mostly focused on private (un-securitized) versus public (securitized) real estate asset classes. Size, property type, geographic and economic regions, urban versus suburban, mortgage versus equity, and common versus preferred stock types in real estate are some of the main groupings for which the literature evaluates their diversification power. This study proposes a new way to categorize within securitized real estates in the form of REITs for the purpose of differential diversification benefits. REITs in the current study are classified according to their dividend payout ratios.

3 DATA AND EMPIRICAL METHODOLOGY

3.1 Data

We use weekly returns on US stock market index (S&P500), FTSE Nareit all REIT index, and REIT firms from January 4, 2000 to December 31, 2022. Both firm and index level data are collected from Refinitiv ESG database. Relying on the ex-post dividend decisions of REITs, we place REITs into two groups of low and high dividend paying firms, using the annual dividend payout ratios. If the dividend payout ratio of a REIT is lower (higher) than the average of all REITs in that year, then we mark that REIT as a candidate for the group with low (high) dividend payments.[2]

We construct a value weighted REIT index for each sub-group based on their dividend payouts; low and high REITs. As there is a 90% minimum dividend requirement for REITs in the US, they can choose to pay around this threshold or they can choose to pay all of their earnings in the form of dividends.[3]

Tab. 1 presents the descriptive statistics of the equity market index, a REIT market index and weighted REIT indices. Our categorization of low and high REITs is meaningful since we create two categories with distinct dividend payout ratios. The table shows that, between the REIT groups, the high REITs group has the higher return and the higher standard deviation, the low REITs group has the lower return and lower standard deviation, which means that the risk-return trade-off concept is in play. Higher standard deviation of the high REITs group is supported by higher returns and lower standard deviation of the low REITs group is supported by lower returns. In terms of the combination of risk and return, the low REITs group has a better performance; return per unit of risk is slightly larger for the low REITs group.

One consideration is the overall correlations between our sub-groups of REITs. If the diversification benefits do change with their dividend payout ratios, then we would expect these sub-groups of REITs to have low or negative correlations with each other and similar correlations with the equity market index. Panel B of Tab. 1 reports the pairwise correlation between the stock market index and the value-weighted indices of REITs. The table shows that both REIT indices have low correlations with the stock market index and negative correlation with each other, which implies that each REIT sub-group has the potential to further diversify the stock market portfolio and the other REIT sub-group.

Between the REIT indices, the high REITs group has the lower pairwise correlation with the stock market index and the higher diversification potential for the stock market investors. One can argue that if a REIT's dividend payout decision is unrelated to its correlation with the stock market index, then we should expect to see no difference in correlations of our REIT sub-groups with the stock market index. However, a two-sample t-test strongly rejects (p-value: 0.000) the null hypothesis of zero difference in correlations of the sub-groups of REITs with the stock market. This is evident for that these sub-groups of REITs are not just randomly selected into their groups. They provide a different and a unique level of diversification.

Further, having negative correlations between the REIT sub-group indices confirms that our way of grouping REITs based on their dividend payout ratios can be used to form REIT subclasses that give unshared diversification benefits. The negative correlations of REIT indices with each other as well as the low correlation with the stock market index signal the possibility of the diversification power of

[2] When REITs that do not consistently classify as low- or high-dividend firms throughout the sample period are excluded due to significant changes in their dividend policies, the unreported results are similar and more robust.

[3] For US REITs, a minimum dividend payout ratio of 90% is applied to taxable income, which is not disclosed. Financial statements are often used to estimate taxable income by increasing net income to its pre-tax value using the statutory tax rate. For example, if a firm has net income of USD 6.5 million and the statutory tax rate is 35% the taxable income would be calculated at USD 10 million (USD 6.5 million/0.65). This example assumes that the firm paid USD 3.5 million in current tax; however, how much tax this firm actually paid is impossible to determine. Several reasons are suggested for why taxable income cannot be estimated using financial statements. Ample evidence in the literature suggests that reported earnings in financial statements can be manipulated upwards or downwards as needed. In addition, financial statements are prepared under business objectives, whereas the tax payable to the Internal Revenue Service is calculated under tax accounting systems. Thus, a firm's reported tax and the actual tax paid to the authorities can be different. Not surprisingly, different sets of rules in different accounting systems with different objectives are expected to produce different incomes. To overcome this problem, the literature suggests multiple methods to estimate taxable income, all of which are prone to errors. Our assumption is that the dividend decision is either unaffected or affected in the same way by the tax rate since all REITs in the US are subject to the same tax rates. Thus, we expect the dividend payout ratio to reflect the firm's dividend policy decisions.

Tab. 1: Descriptive Statistics & Pairwise Correlations
This table presents the descriptive statistics of returns on equity and weighted REIT indices that are created based on their dividend distribution ratios. Weights are chosen based on market capitalization of REITs when indices are formed. Low REITs and High REITs represent REIT indices consisting low-dividend-paying, and high-dividend-paying, respectively. Equity is annualized return on S&P 500 Composite Price Index (S&PCOMP(PI)) and REIT is annualized return on FTSE Nareit All REITs Index (FTFNAR) for the period from Jan 2000 to Dec 2022.

	Equity	**REIT**	**Low REITs**	**High REITs**	**Cash**
Panel A: Descriptive Statistics					
Mean	0.0497	0.0277	0.0729	0.0847	0.0166
Median	0.1236	0.1332	0.1558	0.1858	0.0101
Maximum	5.9403	11.6974	26.2385	64.8078	0.0620
Minimum	−10.4436	−15.8319	−29.6469	−72.3770	−0.0000
Std. Dev.	1.3071	1.9525	2.4572	3.9758	0.0184
Skewness	−0.8678	−0.6589	−0.8779	−0.9450	0.9593
Kurtosis	10.1293	14.4118	46.0878	4.2967	2.5981
Jarque-Bera Test Statistic (10^4)	0.2806	0.5520	9.6934	0.0137	0.0199
N	1248	1004	1248	1248	1248
Div. Payout Ratio			66%	336%	
Panel B: Pairwise Correlations					
Equity	1	0.7522	0.5338	0.2494	−0.0052
REIT		1	0.6542	0.3636	−0.0073
Low REITs			1	−0.3014	−0.0064
High REITs				1	−0.0086

REIT sub-groups to one another as well as to the stock market index investors.

3.2 Mean-Variance Spanning Test

In the first part of our analysis, we test the diversification potential of the overall REIT index as well as the weighted REIT indices to the stock market index portfolio by performing a regression-based spanning test. We use the mean-variance spanning test introduced by Huberman and Kandel (1987), hereafter HK. The main idea behind the mean-variance spanning test is simple. Spanning is the coinciding of the mean-variance efficient frontier of the benchmark assets (a set of K assets) and that of the benchmark assets plus the test assets (a set of $N+K$ assets), in which case test assets do not provide significant diversification benefits over benchmark assets.[4] We assume that the risk-free rate does not exist, or equivalently, risk-free lending and borrowing rates are different. Hence, we investigate the spanning of the minimum variance portfolios rather than a tangency portfolio since investors will be interested in the minimum variance portfolios when they cannot short the risk-free rate.[5]

The assumption is that the stock market portfolio (K) spans a larger portfolio of the stock market plus REITs ($N+K$) if the frontier of the stock market portfolio coincides with the frontier of the stock market plus REITs. If the two frontiers of both smaller and larger portfolios span, then REITs do not provide significant diversification benefits to the stock market.

[4] For a discussion on mean-variance spanning tests, the reader is referred to Kan and Zhou (2012) and Lee and Lee (2010).

[5] When shorting risk-free rate is allowed, the objective of investors is to maximize the Sharpe ratio. In that case they will be interested in the tangency portfolio of risky assets and investigate whether the tangency portfolio from using a set of K benchmark risky assets is identical to the one from using a set $N+K$ test plus benchmark risky assets.

As a first step in formalizing the statistical test of spanning, we define the expected returns (μ) of both asset classes as:[6]

$$\mu = E[r_t] = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \tag{1}$$

and the covariance matrix (V) of the $N+K$ risky assets as:

$$V = \mathrm{Var}[r_t] = \begin{bmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{bmatrix}, \tag{2}$$

where V is assumed to be non-singular. By projecting r_{2t} on r_{1t}, we estimate the following equation:

$$r_{2t} = \alpha + \beta r_{1t} + \epsilon_t, \quad t = 1, 2, \ldots, T, \tag{3}$$

with $E[\epsilon_t] = 0_N$ and $E[\epsilon_t r'_{1t}] = 0_{N\times K}$, where 0_N is defined as N-by-1 vector of zeros and $0_{N\times K}$ is an N-by-K matrix of zeros; r_{1t} and r_{2t} are assumed to be normally distributed.[7] Borrowing the necessary and sufficient conditions for spanning from HK, the null hypothesis of spanning is as follows:

$$H_0: \quad \alpha = 0_N, \quad \theta = 1_N - \beta 1_K = 0_N, \tag{4}$$

where 1_N is defined as an N-by-1 vector of ones. If the null hypothesis is not rejected, then benchmark risky assets are identical to benchmark plus test risky assets, so there is spanning. Benchmark risky assets span benchmark plus test risky assets. However, if the null hypothesis is rejected, then adding the test risky assets to the benchmark risky assets expands the investment universe for the benchmark risky asset investors. In other words, by adding test risky assets investors can shift the minimum variance frontier outward, resulting in portfolios with a reduced risk for similar returns.

To test the null hypothesis given in Eq. 4 for our benchmark asset of the stock market index and test assets of REIT indices, we denote by r_{1t} as the returns on the stock market portfolio (the benchmark risky asset), and by r_{2t} as the returns on REIT indices (the test risky assets). Let r_t represent returns on benchmark plus test risky assets ($N+K$). We run the regression in Eq. 3 under the common assumption that α and β are constant over time. Rewrite Eq. 3 in matrix form for notational convenience as follows:

$$Y = XB + E, \quad E \sim \mathcal{N}(0, \Sigma), \tag{5}$$

where a T-by-N matrix of Y is equal to r_{2t}, a T-by-$(K+1)$ matrix of X is equal to $[1, r'_{1t}]$ with 1 being a size T vector of ones, and a T-by-N matrix of E is equal to E_t. We assume that $T \geq N+K$ and non-singularity of $\chi'\chi$. The disturbances E are assumed to have multivariate normal distribution and Σ is variance-covariance matrix of the disturbances with independent and identically observations. In Eq. 5, the estimator or B is

$$\widehat{B} \equiv \begin{bmatrix} \widehat{\alpha} & \widehat{\beta} \end{bmatrix}' = (X'X)^{-1}(X'Y)$$

and the estimator of Σ is

$$\widehat{\Sigma} \equiv \frac{1}{T}\left(Y - X\widehat{B}\right)'\left(Y - X\widehat{B}\right).$$

Under the normality assumption, we have

$$\mathrm{vec}\,(\widehat{B}') \sim \mathcal{N}\left(\mathrm{vec}\,(\widehat{B}'), (X'X)^{-1} \otimes \Sigma\right).$$

We define $\Theta = \begin{bmatrix} \alpha & \theta \end{bmatrix}'$ and the null hypothesis given in Eq. 4 can be rewritten as

$$\Theta = \begin{bmatrix} \alpha & \theta \end{bmatrix}' = 0_{2\times N} = C - AB,$$

where $A = \begin{bmatrix} -1 & 0'_K \\ 0 & 1'_K \end{bmatrix}$ and $C = \begin{bmatrix} 0'_N \\ 1'_N \end{bmatrix}$.

[6] For convenience, we follow notations and treatments in Kan and Zhou (2012).

[7] In the mean-variance spanning procedure, while small sample tests assuming normality are generally preferred when the normality assumption is met, Kan and Zhou (2012) demonstrate that alternative tests, such as those based on the generalized method of moments (GMM), remain valid even when the data exhibits nonnormality. Although unreported results yield similar findings, we focus on reporting test statistics derived from the regression framework, as they offer more straightforward interpretation and communication.

Using maximum likelihood method, the estimator of Θ is

$$\widehat{\Theta} \equiv \begin{bmatrix} \widehat{\alpha} & \widehat{\theta} \end{bmatrix} = C - A\widehat{B}.$$

For computational ease, we define $\widehat{G}$ and $\widehat{H}$ as follows:

$$\begin{aligned} \widehat{G} &= TA\left(X'X\right)^{-1}A' \\ &= \begin{bmatrix} 1+\widehat{\mu}_1'\widehat{V}_{11}^{-1}\widehat{\mu}_1 & \widehat{\mu}_1'\widehat{V}_{11}^{-1}1_K \\ \widehat{\mu}_1'\widehat{V}_{11}^{-1}1_K & 1_K'\widehat{V}_{11}^{-1}1_K \end{bmatrix}, \end{aligned} \tag{6}$$

$$\begin{aligned} \widehat{H} &= \widehat{\Theta}\widehat{\Sigma}^{-1}\widehat{\Theta}' \\ &= \begin{bmatrix} \widehat{\alpha}'\widehat{\Sigma}^{-1}\widehat{\alpha} & \widehat{\alpha}'\widehat{\Sigma}^{-1}\widehat{\theta} \\ \widehat{\alpha}'\widehat{\Sigma}^{-1}\widehat{\theta} & \widehat{\theta}'\widehat{\Sigma}^{-1}\widehat{\theta} \end{bmatrix}, \end{aligned} \tag{7}$$

where

$$\widehat{\mu}_1 = \frac{1}{T}\sum_{t=1}^{T} r_{1t}$$

and

$$\widehat{V}_{11} = \frac{1}{T}\sum_{t=1}^{T}\left(r_{1t}-\widehat{\mu}_1\right)\left(r_{1t}-\widehat{\mu}_1\right)'.$$

The distribution of the null hypothesis can be verified that

$$\text{vec}\left(\widehat{\Theta}'\right) \sim \mathcal{N}\left(\text{vec}\left(\Theta'\right), (\widehat{G}/T)\otimes\Sigma\right).$$

By defining $U = |\widehat{G}|/|\widehat{H}+\widehat{G}|$, and denoting λ_1 and λ_2 are two eigenvalues of $\widehat{H}\widehat{G}^{-1}$, where $\lambda_1 \geq \lambda_2 \geq 0$, we have $1/U = (1+\lambda_1)(1+\lambda_2)$. The distribution of the asymptotic Wald (W), Likelihood ratio (LR), and Lagrange multiplier (LM) test statistics follows Chi-squared distribution ($\tilde{\chi}^2$) and the null hypotheses can then be written as follows.[8]

$$\text{W} = T(\lambda_1+\lambda_2) \overset{A}{\sim} \tilde{\chi}^2_{2N} \tag{8}$$

$$\text{LR} = T\sum_{i=1}^{2}\ln(1+\lambda_i) \overset{A}{\sim} \tilde{\chi}^2_{2N} \tag{9}$$

$$\text{KM} = T\sum_{i=1}^{2}\frac{\lambda_i}{1+\lambda_i} \overset{A}{\sim} \tilde{\chi}^2_{2N} \tag{10}$$

The test statistics identify whether the inclusion of the REIT index significantly improves the global-minimum variance portfolio. Rejecting the null hypothesis would indicate that a portfolio of the stock market index plus the REIT index has lower risk compared to the conventional stock market portfolio. In other words, a statistically significant shift of the efficient frontier to the left means that the REIT index provides diversification benefits to the stock market index investors, in which case the null is rejected.

3.3 The DCC Model Forecasting

A realistic dynamic portfolio allocation requires out-of-sample forecasting of the ex-ante covariances. In order to forecast ex-ante out-of-sample correlations between the stock market and REIT indices to optimize the global minimum variance portfolio, we use Engle and Sheppard (2001)'s DCC model in a 5-year rolling window framework.

We start by calculating continuously compounded returns:

$$r_{i,t} = \log\left(\text{index}_{i,t}\right) - \log\left(\text{index}_{i,t-1}\right),$$

where $\text{index}_{i,t}$ and r_t denotes the value of index of asset class i and continuously compounded return of the index at time t.[9] The asset class i is either the stock market or one of the REIT indices.

After computing the index returns, the residuals from ARMA(p,q) with appropriate lags are calculated:

$$\begin{gathered} r_{i,t} = \delta_{i,0} + \sum_{k=1}^{p}\delta_{i,1}r_{i,t-k} + \sum_{l=0}^{q}\epsilon_{i,t-l}, \\ \epsilon_{i,t} \sim \mathcal{N}(0,h_{i,t}) \end{gathered} \tag{11}$$

$$\epsilon_{i,t} = \sqrt{h_{i,t}}\eta_{i,t} \tag{12}$$

In Eq. 11, p and q are determined based on Bayesian information criterion (BIC). Residuals are then used in the univariate GARCH and multivariate DCC processes.

Let define a covariance matrix of H_t. The DCC implies that the covariance matrix is the

[8] See Kan and Zhou (2012) for further details.
[9] In this study, return and excess return terms are used interchangeably.

product of conditional correlation matrix of standardized disturbances with the square root of the product of the variances: $H_t = D_t R_t D_t$, where $D_t = \text{diag}\left[\sqrt{h_{ii,t}}\right]$, $h_{ii,t}$ are the variances of residuals and R_t is the conditional correlation matrix of standardized disturbances.

The estimation of the model is made in two steps. First, the variance ($D_t = \text{diag}\left[\sqrt{h_{ii,t}}\right]$) and second, the correlation (R_t) processes are forecasted separately. According to Engle and Sheppard (2001), separate forecasting of variance and correlation gives the least biased forecast.[10]

One-step ahead forecast of conditional variance matrix is:

$$\begin{aligned} E\left[D_{t+1} \mid \mathcal{F}_t\right] = \text{diag}\,(& \sqrt{h_{1,t+1} \mid \mathcal{F}_t}, \\ & \sqrt{h_{2,t+1} \mid \mathcal{F}_t}, \\ & \vdots \\ & \sqrt{h_{n,t+1} \mid \mathcal{F}_t}) \\ = & \begin{bmatrix} h_{1,t+1|t} & \cdots & \cdots \\ \vdots & \ddots & \vdots \\ \cdots & \cdots & h_{n,t+1|t} \end{bmatrix}, \end{aligned}$$

$\epsilon_{i,t}$ is assumed as a process that is a univariate GARCH. Therefore, GARCH (1,1) model is defined as follows:

$$h_{i,t+1} = \omega_i + \alpha_i \epsilon_{i,t}^2 + \beta_i h_{i,t} \tag{13}$$

Eq. 13 defines the time-varying volatility process; $h_{i,t+1}$ is one-step ahead forecast of conditional variance of the disturbances; $\epsilon_{i,t}$ is the innovation of asset i at time t; i is the stock market index, or REIT indices. Coefficients are restricted with non-negativity to ensure the volatility process is always positive; the intercept, the coefficient of past shocks α and that of past conditional variance β are all restricted to positive. Also, $\alpha_i + \beta_i < 1$ ensures that the process is stationary.

Rather than being a forecast by itself, the one-step ahead forecast of conditional correlation matrix R_{t+1} is the ratio of the covariance forecast to the square root of the product of variances forecasts.

[10]See Orskaug (2009) for further details.

The one step-ahead forecast of correlation matrix conditional on the information set of $\mathcal{F}_t$ is:

$$E\left[R_{t+1}|\mathcal{F}_t\right] = \text{diag}\left(Q_{t+1}^{-1/2}\right) Q_{t+1} \text{diag}\left(Q_{t+1}^{-1/2}\right)$$

$$\begin{bmatrix} \frac{1}{\sqrt{q_{11,t+1}}} & \cdots & \frac{1}{\sqrt{q_{1m,t+1}}} \\ \vdots & \ddots & \vdots \\ \frac{1}{\sqrt{q_{n1,t+1}}} & \cdots & \frac{1}{\sqrt{q_{nm,t+1}}} \end{bmatrix} \cdot$$

$$\cdot \begin{bmatrix} q_{11,t+1} & \cdots & q_{1m,t+1} \\ \vdots & \ddots & \vdots \\ q_{n1,t+1} & \cdots & q_{nm,t+1} \end{bmatrix} \cdot$$

$$\cdot \begin{bmatrix} \frac{1}{\sqrt{q_{11,t+1}}} & \cdots & \frac{1}{\sqrt{q_{1m,t+1}}} \\ \vdots & \ddots & \vdots \\ \frac{1}{\sqrt{q_{n1,t+1}}} & \cdots & \frac{1}{\sqrt{q_{nm,t+1}}} \end{bmatrix} =$$

$$= \begin{bmatrix} 1 & \cdots & \rho_{1m,t+1} \\ \vdots & \ddots & \vdots \\ \rho_{n1,t+1} & \vdots & 1 \end{bmatrix},$$

where Q_{t+1} is the variance-covariance matrix, in which q_{ij}, q_{ii} and q_{jj} are the forecast elements, where q_{ij} being the covariance matrix, with q_{ii} and q_{jj} being the variance of assets i and j: h_i and h_j, respectively. The typical element of R_{t+1} will be of the form

$$\rho_{ij} = \frac{q_{ij}}{\sqrt{h_i}\sqrt{h_j}}.$$

Thus, the DCC (1,1) forecasting model of covariance is as follows:

$$q_{ij,t+1} = (1 - a - b)\overline{\varrho_{ij}} + a\eta_{i,t}\eta_{i,t} + bq_{ij,t}, \tag{14}$$

$$\eta_{i,t} = \epsilon_{i,t} D_{i,t}^{-1} = \frac{\epsilon_{i,t}}{\sqrt{h_{i,t}}}, \tag{15}$$

where $q_{ij,t}$ is the one-step ahead forecast of covariance, $\overline{\varrho_{ij}}$ is the unconditional correlation between the residuals of market i and j, and standardized disturbances, $\eta_{i,t}$, are derived from the first step estimation of conditional volatility. Coefficients a and b represent the effect of past shocks and past conditional covariance on current covariance. The reverting process implies $a+b<1$ and the non-negativity of coefficients a and b. The persistence of the correlation gets stronger as the sum of the two coefficients gets closer to 1.

The conditional correlations are obtained using the conditional variances from the first stage via GARCH (1,1) model that runs for each time series separately and conditional covariance from the second stage via DCC (1,1) model that runs for all-time series at once:

$$\rho_{ik,t+1} = \frac{q_{ij,t+1}}{\sqrt{h_{i,t+1}}\sqrt{h_{j,t+1}}},$$

where $\rho_{ik,t+1}$ represents one-step ahead forecast of conditional correlations.

3.4 Rolling Window Correlation Model

To serve as a benchmark model for the DCC model, the correlation forecast for $t+1$ is derived using a rolling window approach. Specifically, the correlation between asset classes for the next period is estimated as the pairwise correlation calculated over a rolling window of the last 5 years of data, up to time t.

This method assumes that the correlation structure between asset classes remains relatively stable over the short-term, and the most recent correlations provide the best estimate for the immediate future. Mathematically, the correlation at time $t+1$, ρ_{t+1}, is given by:

$$\rho_{t+1} = \text{Corr}\left(r_i, r_j \mid \tau - 5 \text{ years } \leq \tau \leq t\right),$$

where r_i and r_j represent the returns of asset classes i and j, respectively. The correlation is calculated using data from the most recent 5-year period leading up to time t.

This rolling window approach is useful in capturing time-varying correlations, as it adapts to changes in the underlying relationship between asset classes over time. By comparing the results of this model with more sophisticated models like the DCC model, we can evaluate the performance of different forecasting methods in predicting future correlations.

The main implication of the Rolling Window Correlation Model is that it assumes returns do not follow a specific data-generating process, making it a valuable null hypothesis in financial studies. If a more advanced model, such as the DCC model, outperform the Rolling Window Correlation Model in forecasting correlations, it indicates that this model is capturing additional information beyond what the rolling window method accounts for.

In our analysis, we compare the forecasting performance of the DCC model against the Rolling Window Correlation Model to evaluate whether the DCC model provides superior predictions of future asset correlations and portfolio optimizations.

3.5 Global Minimum Variance Portfolio Optimization

After documenting the statistical evidence for the diversification benefits of our sub-groups of REITs using a mean-variance spanning test, in this section, we choose the global minimum variance portfolio to evaluate and compare the economic values of the portfolios. We form dynamic portfolios consisting of the stock market index and our weighted REIT indices, one at a time, using both ex-ante and ex-post out-of-sample forecasts of variance-covariance matrix from the DCC and rolling window correlation models.

Built on Markowitz (1952)'s assumptions, modern investment theory assumes that investors are concerned solely with the mean and variance of the probability distribution of their portfolio return. Given this, we assume that portfolios providing minimum variance warrant consideration for investors. Hence, we use a mean-variance procedure to form portfolios.[11]

The classical optimization of the global minimum variance can be formulated as follows:

[11] Mean-variance procedures are special cases of the more general expected utility formulations. We justify the mean/variance procedure by assuming that all relevant probability distributions are same and that investors have a quadratic utility function; investors prefer more return to less. Levy and Markowitz (1979) shows that there is a very high probability that portfolios formed based on mean-variance criteria and maximizing the expected utility for a variety of utility functions would lead similar results.

$$\min_{w_{t,t+k}} \sigma_{p,x}^2 = w'_{t,t+k} H_{t,t+k} w_{t,t+k}, \quad (16)$$

$$w'_{t,t+1}\mu = \mu_0,$$

$$\text{subject to } \sum_{i=1}^{N} w_{t,t+1} = 1,$$

where $i = 1, \ldots, m$ and $w_{t,t+k}$ is the vector of portfolio weights for time $t+1$ chosen at time t, $H_{t,t+k}$ is the conditional covariance matrix for time $t+1$ of returns, $r_{t,t+k}$ index log return from time t to time $t+k$, μ is assumed to be the vector of returns of risk-free assets, and finally $\mu_0 > 0$ is the required rate of return. Thus, the solution to Eq. 16 is:

$$w_{t,t+k} = \frac{H^{-1}_{t,t+k}\mu}{\mu' H^{-1}_{t,t+k}\mu}\mu_0,$$

where $w_{i,t+k}$ is an element of the optimized weight in vector $w_{t,t+k}$ and the portfolio share of asset i at time $t+k$ and $1 - \sum_{i=1}^{N} w_{i,t+k}$ is the share of risk-free asset in the portfolio. The corresponding portfolio return and variance are $w'_{t,t+k} r_{t,t+k}$ and $w'_{t+t+k} H_{t,t+k} w_{t,t+k}$, respectively. Coefficient k is equal to 0 for ex-post and 1 for ex-ante portfolio optimization.

We use a 5-year rolling window to forecast ex-ante covariances and then allocate the optimal weights based on this covariance matrix. Optimization uses the first five years (January 2000 to December 2004) to estimate coefficients. Therefore, we observe our REIT sub-groups' diversification behavior during and after the global financial crisis as we allocate our portfolio.

4 EMPIRICAL RESULTS

This section reports the empirical results from the mean-variance spanning test results and the analysis on ex-ante portfolio allocation in global minimum variance portfolio framework. However, we should note here that our portfolio allocation is different from traditional portfolio allocation. An investor who seeks to minimize the risk of their portfolio would generally diversify it by allocating the total capital among various financial securities, industries, and other categories. However, since our aim in this study is to investigate the relationship between the diversification power of REITs and their dividend payout policies, we limit the asset classes in our portfolio allocation to stock market and REITs only. We first create sub-groups of REITs based on their dividend payout ratios and add these sub-groups into the market portfolio. This way of portfolio setup can help us to identify the effect on the diversification benefits from the specified REIT sub-group, which is the main goal in this study. If dividend payouts are unrelated to REITs diversification benefits, then we should expect to see no significant change in the performance of the portfolio.

Generally, the findings of this study align with existing literature such as Burns and Epley (1982) and Sa-Aadu et al. (2010). That is, REITs expand the efficient frontier, which enhances portfolio efficiency. In addition, our research also introduces novel insights into REITs' role in portfolio diversification. This is, when dividend payout ratios are used to categorize REITs, the diversification benefits of these stocks vary. When using advanced forecasting models, such as the DCC model, high-dividend-paying REITs offer greater diversification benefits than low-dividend-paying REITs.

In detail, Pacholec (2022) demonstrated that certain REIT sectors consistently offered superior diversification benefits across different market conditions, and Badji et al. (2021) confirmed that sector-specific and sub-group diversification can provide varying levels of diversification benefits. We show that REIT subgroups, created by dividend payout ratios, also provide unique diversification benefits and that high-dividend-paying REITs perform better in providing diversification than low-dividend-paying REITs, adding another dimension to portfolio optimization. There are a number of studies arguing that certain sectors, like logistics and apartments, are better diversifiers than others, regardless of their dividend payout policies. This study provides a new layer of insight into the characteristics that contribute to the diversification power of REITs.

Earlier studies such as Huang and Zhong (2013) and Fugazza et al. (2007) examined the diversification benefits of REITs using both ex-post and ex-ante portfolio models. Fugazza et al. (2007) found significant ex-post benefits when including REITs in portfolios. According to Huang and Zhong (2013), the 2008 financial crisis impacted REIT diversification. Using both ex-post and ex-ante models (rolling window correlation and DCC), we find that the DCC model consistently outperforms the rolling window model by generating portfolios with higher Sharpe ratios and lower standard deviations. Additionally, the study confirms that REITs' diversification benefits are dynamic, as they offered strong benefits pre- and during the 2008 financial crisis, but lost their diversification potential post-crisis. This echoes Huang and Zhong (2013)'s findings regarding financial crises' impact on asset diversification roles.

Our study provides a significant addition to the literature by showing that advanced forecasting models such as the DCC are not only superior to traditional methods at capturing time-varying correlations but also enhance portfolio performance. Its ability to produce better risk-adjusted returns and lower portfolio volatility aligns with the findings of Fugazza et al. (2007) regarding the importance of advanced modeling techniques. Furthermore, Marzuki and Newell (2021) found that REITs provided diversification benefits during the pandemic, despite higher volatility. Likewise, our study shows that REITs, particularly low-dividend-paying REITs, contributed significantly to diversification during the Covid-19 crisis.

4.1 Mean Variance Spanning Test Results

We use Huberman and Kandel (1987)'s Spanning Test to investigate equity REITs (test assets) diversification benefits for investors of the stock market (benchmark assets). By not allowing short selling, we aim to keep the focus on the shift in the efficient frontier purely for REIT related reasons and not capital market efficiencies or inefficiencies due to unobserved reasons.

To examine the diversification benefits over time, we divide our sample into four distinct sub-periods, using the onset and conclusion of the 2008 financial crisis as temporal benchmarks: pre-crisis, peri-crisis, and post-crisis. Additionally, we include the Covid-19 pandemic as a separate sub-sample. This sub-sampling approach is guided by existing literature, which emphasizes the importance of diversification benefits during recent financial crises.

We test the null hypothesis of spanning using asymptotic tests; Wald (W), likelihood ratio (LR), and the Lagrange multiplier (LM). The empirical test statistics of the spanning test at index and firm levels are given in Tab. 2 and 3. The columns in the table are reserved for benchmark assets. Our initial benchmark asset is the stock market index and cash, which is presented in the first three columns. Columns 4 through 6 assume that the benchmark assets are the stock market index, cash and an index representing low dividend- paying REITs while the test assets are high-dividend-paying REITs. Columns 7 through 9 assume that the benchmark assets are the stock market index, cash and an index representing high dividend-paying REITs while the test assets are low-dividend-paying REITs in this case. The rows of the table are reserved for the test assets of the spanning test. The first row of each panel in the table assumes that the test asset is an index representing all REITs in the country. The second and third rows of each panel in the table assumes that the test asset is an index representing high- and low-dividend-paying REITs.

4.1.1 Aggregate Index Level Spanning Test

We test whether the stock market investors can diversify their portfolio further by investing in an index of all REITs, or two indices of grouped REITs. Empirical results in Tab. 2 Panel A reports the full sample results. When all REITs are considered, the spanning test results show that the index representing all the REITs improves the efficient frontier when combined

Tab. 2: Mean-Variance Spanning Tests of REIT Portfolios at Index Level
This table presents the actual probabilities for the rejection of three asymptotic tests of spanning, Wald (W), likelihood ratio (LR), and Lagrange multiplier (LM), under the null hypothesis for different REIT groups. The asymptotic p-values of all three tests are set at 5% based on the asymptotic distribution of $\tilde{\chi}^2$ and actual p-values in brackets are based on their finite sample distributions under normality assumption.

	Equity			Equity + Low REITs			Equity + High REITs		
Test Assets	**W**	**LR**	**LM**	**W**	**LR**	**LM**	**W**	**LR**	**LM**
Panel A: Full Sample									
Index of All REITs	1301.36	834.63	24498.00						
	[0.000]	[0.000]	[0.000]						
Index of High REITs	121.03	115.60	27221.00	14.77	14.71	0.360			
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
Index of Low REITs	345.94	305.75	46308.00				21.68	21.53	0.092
	[0.000]	[0.000]	[0.000]				[0.000]	[0.000]	[0.762]
Panel B: Pre-2008 Financial Crisis									
Index of All REITs	153.73	110.78	1276.00						
	[0.000]	[0.000]	[0.259]						
Index of High REITs	147.96	127.07	22654.00	13.73	13.57	56002.00			
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
Index of Low REITs	17.39	45613.00	6036.00				1.66	1.66	52.212
	[0.000]	[0.000]	[0.014]				[0.198]	[0.197]	[0.000]
Panel C: Peri-2008 Financial Crisis									
Index of All REITs	119.82	74.45	2941.00						
	[0.000]	[0.000]	[0.086]						
Index of High REITs	28.68	45651.00	19.41	26.09	23.14	29.50			
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
Index of Low REITs	104.77	68.64	0.621				49.99	39.81	13.552
	[0.000]	[0.000]	[0.431]				[0.000]	[0.000]	[0.000]
Panel D: Post-2008 Financial Crisis									
Index of All REITs	437.98	322.19	0.031						
	[0.000]	[0.000]	[0.859]						
Index of High REITs	66.20	62704.00	15612.00	3.07	3.07	10.406			
	[0.000]	[0.000]	[0.000]	[0.080]	[0.079]	[0.001]			
Index of Low REITs	123.05	111.34	95694.00				2.54	2.54	24.78
	[0.000]	[0.000]	[0.000]				[0.111]	[0.111]	[0.000]
Panel E: Peri-Covid-19									
Index of All REITs	466.56	246.11	7104.00						
	[0.000]	[0.000]	[0.008]						
Index of High REITs	1999.00	45293.00	0.563	60.88	53.86	0.095			
	[0.157]	[0.156]	[0.453]	[0.000]	[0.000]	[0.758]			
Index of Low REITs	62.16	54.85	5538.00				77.14	66.16	2.049
	[0.000]	[0.000]	[0.168]				[0.000]	[0.000]	[0.152]

with the stock market index and cash. Further, we document that our sub-groups of REITs provide different diversification benefits. The index of both high- and low-dividend-paying US REITs provides diversification benefits to the US stock market investors in the full sample. The sub-group analysis also reports that the diversification potential of REITs is associated with REITs dividend policy. Moreover, the index of low-dividend-paying REITs (test assets) enhances portfolio diversification not only when combined with the stock market index and cash (benchmark assets) but also when included in portfolios alongside the stock market index, cash, and the index of high-dividend-paying REITs (benchmark assets). Similarly, high-dividend-paying REITs (test assets) offer distinct diversification benefits when added to portfolios containing the stock market index, cash, and low-dividend-paying REITs (benchmark assets).

In the pre-2008 financial crisis period, as shown in Panel B, the equity REIT index, along with indices of sub-grouped REITs, has the potential to shift the efficient frontier. Our mean-variance spanning test results contribute to the existing literature by indicating that the U.S. REIT index offered diversification benefits during the 2008 global financial crisis, contrasting with the findings of Huang and Zhong (2013). Additionally, Panel D reveals that post-crisis, low-dividend-paying REITs gained in diversification potential. During the Covid-19 period, the index representing all REITs and low-dividend-paying REITs continued to provide diversification benefits for stock market investors, whereas high-dividend-paying REITs experienced a decline in their diversification effectiveness.

Our index level analysis makes several contributions to the literature. First, we identify that diversification produced by indices representing all REITs exist. We also document evidence at index level for the diversification benefits of a REIT sub-group. Empirical analyses indicate that the indices of low- and high-dividend- paying REITs have unique diversification benefits.

These results provide evidence that our REITs indices can contribute a different type of diversification when compared to the overall REIT index or to the other index of sub-grouped REITs. Moreover, during the 2008 financial crisis and the Covid-19 pandemic period, our REIT indices are an attractive asset class due to their diversification potentials. Our indices representing sub-groups of REITs are value-weighted, and can be considered as a portfolio of these firms with somehow fixed weights of REIT firms relative to market capitalization.[12] Assigning fixed weights to firms in a portfolio may not represent the most efficient approach to portfolio optimization. We posit that such a constraint could potentially reduce the diversification benefits within our REIT groups. Consequently, in the subsequent section, we will relax this restriction by allowing the covariance matrix of individual REIT firms to dictate the weighting of each REIT within the optimal portfolio. This approach will more accurately reflect the true diversification potential of individual REIT firms and the grouped REITs.

4.1.2 Individual Firm Level Spanning Test

We next test the diversification power of individual REITs in each sub-group. We test whether the stock market investors can diversify their portfolio further by investing in REITs, or two sub-groups REITs individually. Like the index level analysis in the previous section, our initial benchmark assets for the spanning test are the stock market index and cash while test assets in this case are individual REITs. Later, the test assets are REITs in low and high sub-groups.

Tab. 3 reports the evidence for firm level REIT diversification.[13] In Panel A, consistent with the findings at the index level, both aggregate REITs and segmented REIT sub-groups demonstrate diversification benefits for stock market investors, with the firm-level analysis showing even stronger significance. Furthermore, each REIT sub-group offers diversification advantages to stock market investors, regardless of the inclusion of the other REIT sub-group. Specifically, during the Covid-19 period, high-REITs also contribute to diversification at the firm level.

We argue that our sub-grouping of REITs does not just randomly divide REITs into different groups, but does so to give each REIT sub-group a unique diversification potential. If we assume that each group of REITs examined

[12] When REIT index level data is used in portfolio formation, the portfolio weight of each REIT in that specific group is forced to be related to its weight in the value-weighted index, which may not be the optimal weight for a REIT firm in the index.

[13] When portfolios are formed using firm level REIT data, the portfolio weight of each REIT is allowed to take any weight. Using firm level REIT data gives more flexibility in order to show the differential diversification power of REIT sub-groups.

Tab. 3: Mean-Variance Spanning Tests of REIT Portfolios at Firm Level
This table presents the actual probabilities for the rejection of three asymptotic tests of spanning, Wald (W), likelihood ratio (LR), and Lagrange multiplier (LM), under the null hypothesis for different REIT groups. The asymptotic p-values of all three tests are set at 5% based on the asymptotic distribution of $\tilde{\chi}^2$ and actual p-values reported in the table are based on their finite sample distributions under normality assumption.

	Equity			**Equity + Low REITs**			**Equity + High REITs**		
Test Assets	**W**	**LR**	**LM**	**W**	**LR**	**LM**	**W**	**LR**	**LM**
Panel A: Full Sample									
Index of All REITs	3897.96	1909.70	159.02						
	[0.000]	[0.000]	[0.716]						
Index of High REITs	2870.02	1617.5	142.58	5589.55	2271.1	148.73			
	[0.000]	[0.000]	[0.906]	[0.000]	[0.000]	[0.000]			
Index of Low REITs	3171.27	1692.2	159.12				5739.82	2279.7	179.36
	[0.000]	[0.000]	[0.216]				[0.000]	[0.000]	[0.032]
Panel B: Pre-2008 Financial Crisis									
Index of All REITs	739.97	494.63	95.224						
	[0.000]	[0.000]	[0.360]						
Index of High REITs	553.19	398.79	57.438	994.15	565.09	58.559			
	[0.000]	[0.000]	[0.878]	[0.000]	[0.000]	[0.854]			
Index of Low REITs	552.16	401.31	116.79				774.71	493.96	117.46
	[0.000]	[0.000]	[0.001]				[0.000]	[0.000]	[0.001]
Panel C: Peri-2008 Financial Crisis									
Index of All REITs	2097.27	532.29	78.412						
	[0.000]	[0.000]	[0.843]						
Index of High REITs	813.15	323.67	49.94	1791.02	406.64	54.878			
	[0.000]	[0.000]	[0.901]	[0.000]	[0.000]	[0.785]			
Index of Low REITs	1338.90	360.26	50.359				4143.49	480.66	52.142
	[0.000]	[0.000]	[0.721]				[0.000]	[0.000]	[0.658]
Panel D: Post-2008 Financial Crisis									
Index of All REITs	2124.35	1009.3	156.74						
	[0.000]	[0.000]	[0.296]						
Index of High REITs	1493.52	839.32	120.47	2628.65	1094.8	124.08			
	[0.000]	[0.000]	[0.827]	[0.080]	[0.000]	[0.759]			
Index of Low REITs	1757.69	892.35	141.18				3467.19	1208.00	119.82
	[0.000]	[0.000]	[0.081]				[0.000]	[0.000]	[0.462]
Panel E: Peri-Covid-19									
Index of All REITs	1228.99	734.8	157.85						
	[0.000]	[0.000]	[0.739]						
Index of High REITs	981.46	547.64	117.8	2922.28	764.41	110.58			
	[0.000]	[0.000]	[0.789]	[0.000]	[0.000]	[0.902]			
Index of Low REITs	1156.68	562.38	116.99				1767.36	645.69	124.44
	[0.000]	[0.000]	[0.659]				[0.000]	[0.000]	[0.152]

here are only a representation of the general REIT market, it is not a surprise to see that sub-groups of REITs provide diversification benefits to the stock market index investors, given that all REITs also provide diversification to the stock market index. However, columns 4 through 9 in Panel A in the table show that all sub-groups of REITs provide diversification to the stock market index as well as other sub-groups of REIT firms, confirming that each sub-group of REITs has its own unique diversification ability. This is an important finding that further supports the index level analysis. When investors are given the freedom to determine the allocation weights of each REIT firm, both categories of REITs demonstrate a unique and

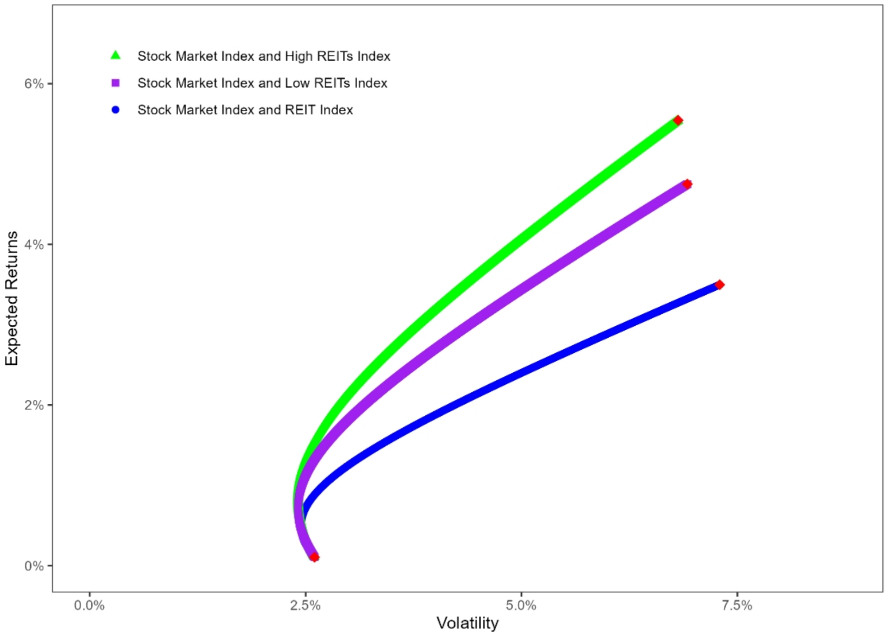

Fig. 1: Mean-Variance Efficient Frontier – Full Sample

statistically significant capacity to enhance the diversification of a stock market portfolio.

Panel B of Tab. 3 shows that the diversification potential of all REITs together and sub-grouped REITs is also highlighted in the pre-2008 financial crisis period. For all combinations of benchmark and test risky assets of equity market index and REIT indices, all three test statistics reject the null hypothesis of spanning, meaning that REIT diversification is present in this time period.

During the financial crisis period, Panel C of Tab. 3, the diversification potential of all individual REITs is consistent across the two sub-groups. High- and low-dividend-paying REITs continue being a good vehicle for diversifying a stock market portfolio. The diversification benefits of REITs are not limited by the choice of dividend payout policy when the US stock market index investors need it most. Furthermore, in the post-2008 global financial crisis period, Panel D, REITs continue to be a good source of diversification for stock market investors.

The analysis of our sub-groups of REIT firms across different sub-periods reveals that all individual REITs within these sub-groups contributed to diversification benefits relative to the stock market index before the financial crisis. However, following the crisis, only REITs characterized by high dividend payouts lost their diversification effectiveness within the portfolio that includes the stock market index, cash, and low-dividend-paying REITs.

We proceed by illustrating the impact of REIT sub-groups on the efficient frontier. Fig. 1 compares the efficient frontiers derived from the stock and REIT market indices and those from a combined stock market index with the index of REIT sub-groups. As shown in Panel A, the inclusion of REIT indices results in a notable alteration of the efficient frontier. Specifically, REIT sub-groups shift the efficient frontier upward, suggesting that investors can construct portfolios with higher expected returns for an equivalent level of risk. Notably, while the low-REITs index offers additional diversification advantages compared to the general REIT index, the high-REITs index provides the greatest

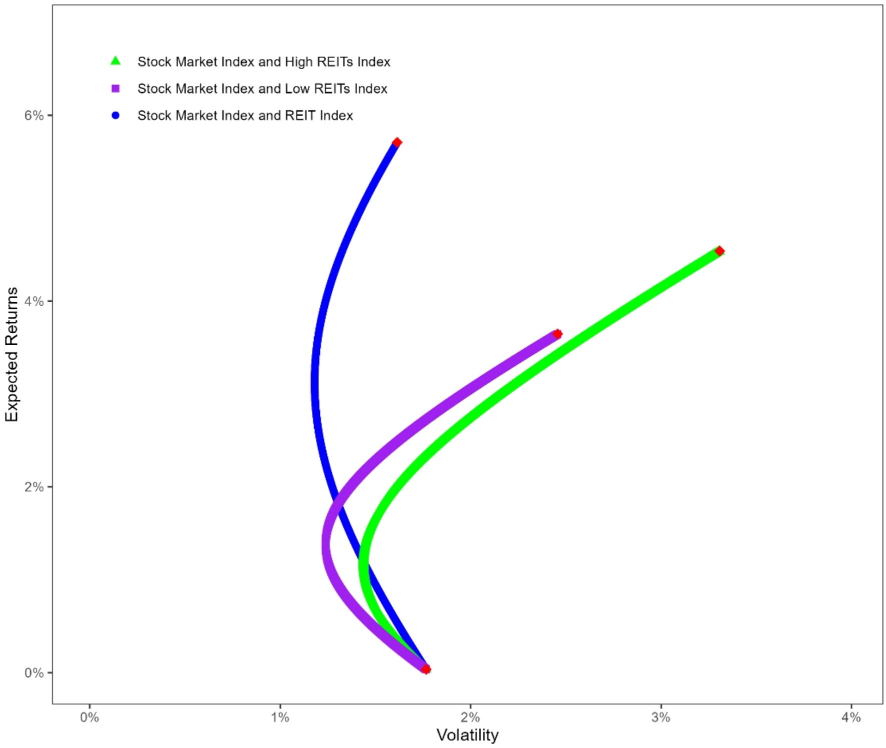

Fig. 2: Mean-Variance Efficient Frontier – Pre-2008 Financial Crisis Period

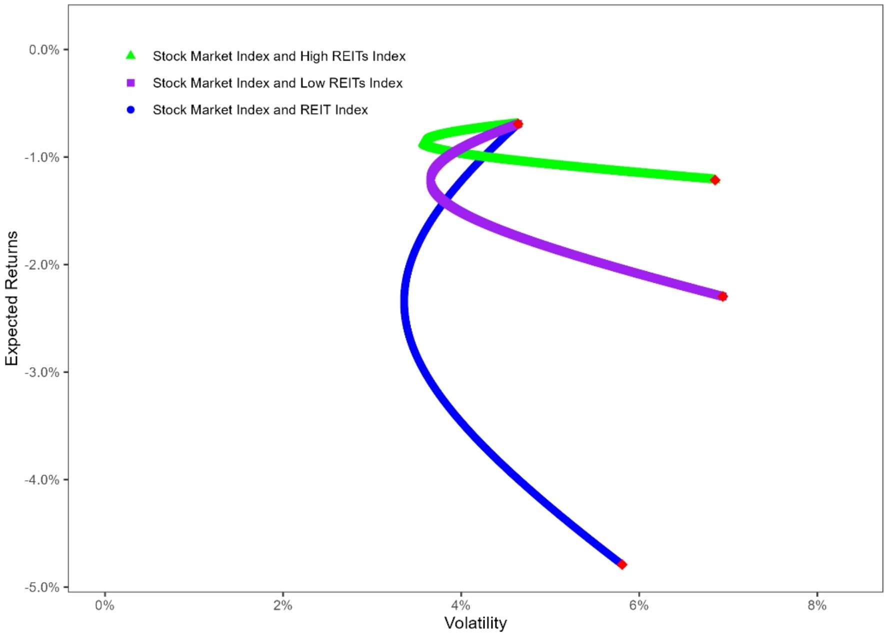

Fig. 3: Mean-Variance Efficient Frontier – Peri-2008 Financial Crisis Period

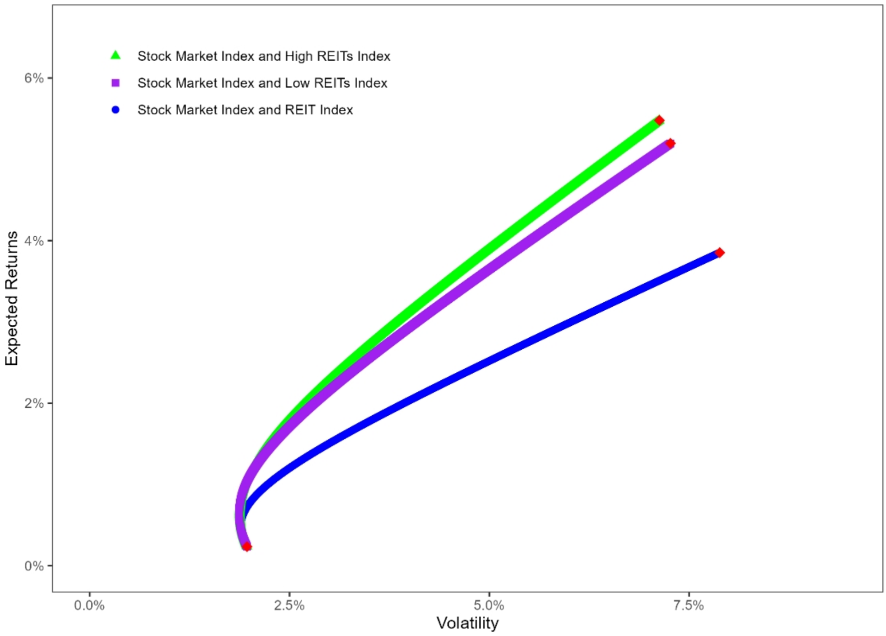

Fig. 4: Mean-Variance Efficient Frontier – Post-2008 Financial Crisis Period

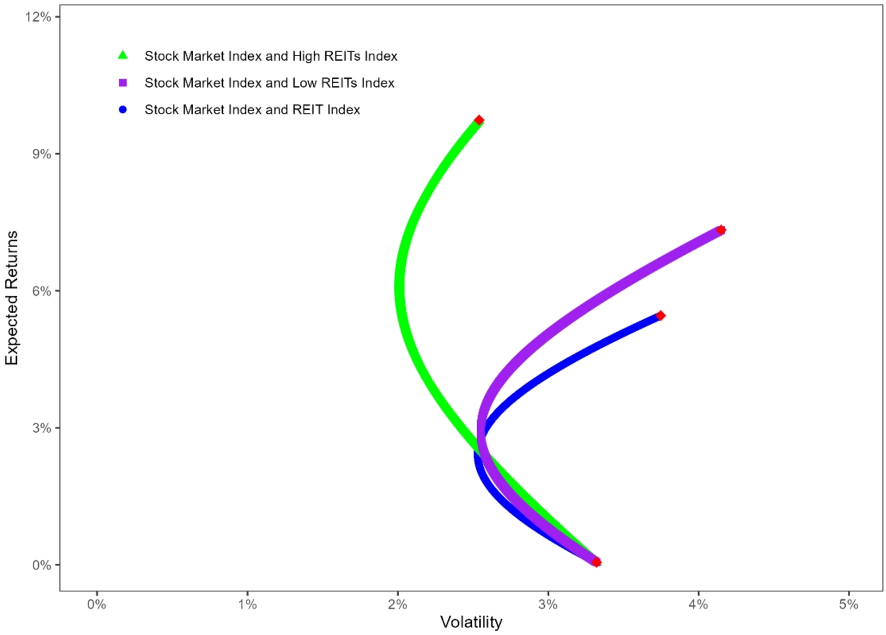

Fig. 5: Mean-Variance Efficient Frontier – Peri-Covid-19 Pandemic Period

diversification benefits. Panels B through E of Fig. 1 display the efficient frontiers for various sub-periods. The findings from the full sample analysis are corroborated across these sub-periods, demonstrating that each REIT sub-group continues to provide a unique level of diversification.

The results of the spanning tests indicate a shift in the efficient frontier at both the index and firm levels.[14] However, this shift appears to be statistically significant but does not necessarily translate into economically meaningful benefits. The figure only suggests that economic gains from portfolio optimization are achievable when considering either all REITs or specific REIT sub-groups.

An opposing viewpoint to our findings could argue that any inclusion of an asset class in a stock market portfolio is likely to enhance the efficient frontier, potentially attributing the improvements observed in this study to the idiosyncratic risk associated with REITs. However, the primary aim of this research is to assess whether the varying diversification benefits of REIT sub-groups, categorized by their dividend payout ratios, hold economic significance. Therefore, our analysis centers on the differences in efficient frontiers when distinct REIT sub-groups are integrated into the stock market portfolio.

Next, we present efficient frontiers of portfolios consisting the equity market index and REIT market indices. Fig. 1 through 5 report the efficient frontiers at index level for the full sample, pre-2008 financial crisis, peri-2008 financial crisis, post-2008 financial crisis, and peri-Covid-19 periods, respectively. Low REITs and High REITs represent indices of low-dividend paying and high-dividend paying REIT firms, respectively.

It is anticipated that the impact of idiosyncratic risk on the variations in efficient frontiers between portfolios comprising different REIT sub-groups is minimal. To further substantiate the economic advantages of diversifying with REIT sub-groups, we proceed to calculate the expected returns, standard deviations, and Sharpe ratios of these portfolios in the subsequent section.

4.2 Portfolio Allocation

Given the statistical and visual evidence of the diversification potential of REITs at both index and firm levels, our analysis points to the following conclusion: REITs provide diversification benefits and the diversification capacity is unique for each of the REITs sub-groups. However, whether these sub-groups actually diversify the stock market portfolio in a real-world portfolio optimization scenario is a question that requires further investigation. We next examine global minimum variance portfolios consisting the stock market index and our sub-grouped REIT indices or individual firms.[15]

Short-sales are not allowed since we optimize global minimum variance portfolios. Portfolios are optimized using ex-post estimates and ex-ante forecast of covariance matrix from two different models. We choose a traditional and comparatively simpler forecasting model (rolling window correlation model) and a more recent and more complicated model (DCC model) to forecast the covariance matrix to be used in portfolio optimization.

Our portfolio optimization starts at the beginning of 2005 because we use the first 5 years of the data to estimate the initial coefficients of the model necessary for both ex-post and ex-ante covariance matrix. We use a 5-year rolling window to estimate ex-post and forecast ex-ante covariance matrices at each point in time after the first estimation. Thus, we are able to document the diversification opportunities of REIT market at both index and firm levels for the period covering the 2008 financial crisis and its afterwards. Additionally, we have extended our analysis to explore the diversification potential during the recent Covid-19 pandemic.

This framework allows us to investigate the following research questions: Can REIT sub-

[14] Firm level efficient frontiers are not reported due to their similarity to the index level efficient frontiers.

[15] We excluded cash from portfolio allocation to further focus on REIT market's diversification potential. However, portfolios consisting of cash, in addition to the stock market and sub-grouped REITs produce qualitatively similar results.

groups provide ex-ante diversification benefits at index and firm levels? If so, which sub-group of REITs produces the most efficient global minimum variance portfolio? What is the function of the forecasting model? Specifically, does employing a more complex model yield benefit? Lastly, we examine whether the diversification advantages provided by our sub-grouped REITs remain stable over time and how they evolve during periods of economic downturns.

Using index and firm level data, Tab. 4 reports expected returns, standard deviations, and Sharpe ratios of portfolios of the stock market and REITs. Columns 1 and 2 of the table displays ex-post and ex-ante global minimum variance portfolio statistics using the rolling window correlation model. Columns 3 and 4 use the DCC model to optimize the portfolios in ex-post and ex-ante frameworks. Descriptive statistics of portfolios formed using REIT indices are reported in Panel A and the portfolios in Panel B are formed using individual REITs.

An important observation of the table is that considerable differences exist in expected returns/risk relationships of the portfolios consisting of different sub-groups of REITs. Panel A of the table presents the statistics for the global minimum variance portfolio utilizing index-level data, while Panel B provides these statistics based on firm-level data. According to the ex-post optimization with rolling window covariance forecasting model, a stock market portfolio that also includes the index of low-, and high- dividend-paying REITs would produce around 4.57%, and 4.85% annual expected return while the standard deviations for these portfolios is 16.78% and 16.64%. The DCC model expected returns on the portfolios are similar to that of rolling window correlation model, but standard deviations are smaller, 14.92% and 14.78%, respectively. Compared to the rolling window correlation model, the DCC model produces portfolios with smaller standard deviations, which points to superiority of the latter. The superior Sharpe ratios observed with the DCC model (0.42 compared to 0.35 for the rolling window model) underscore the enhanced performance and benefits of utilizing this approach. The results indicate that the REIT sub-indices formed based on dividend payouts have different diversification powers and the DCC model produces more efficient portfolios.

Further, we document that the index of high-dividend-paying REITs provides the largest diversification benefits; high-dividend-paying REIT indices have higher Sharpe ratios than low-dividend-paying REIT indices. The superiority of the index of high-dividend-paying REITs in portfolio optimization does not change when using the covariance matrix ex-post estimates or ex-ante forecasts from both models.

Panel B of Tab. 4 gives global minimum-portfolio statistics using firm level data. In accordance with our analysis using index level data, we observe similarities in the expected returns of portfolios consisting of the stock market index plus a REIT sub-index of low- or high-dividend-paying firms while standard deviations do change greatly between the two methods. The DCC model shows a higher Sharpe ratio (0.4292) compared to the rolling window model (0.3674). This suggests that including individual REIT firms, as opposed to REIT indices, under the DCC model, can enhance portfolio performance. The highest Sharpe ratio is observed in the portfolio of stock market index with high-dividend-paying REITs under the DCC model (0.5222), indicating that high REIT firms combined with stocks offer significant diversification benefits. In the portfolio of stock market index with low-dividend-paying REITs, the DCC model again performs better, with a Sharpe ratio of 0.5132, compared to 0.4178 in the rolling window model. This confirms the effectiveness of the DCC model in managing portfolios with low REITs.

The DCC model consistently outperforms the rolling window model across all scenarios, offering better risk-adjusted returns as evidenced by higher Sharpe ratios. This suggests that the DCC model's ability to dynamically adjust correlations results in more effective diversification and improved portfolio performance. Portfolios that include high-payout REITs tend to show better performance in terms of Sharpe ratios, particularly when using the DCC model.

Tab. 4: Global Minimum Variance Portfolio Statistics – Weekly Index and Firm Level Data
This table presents expected returns, standard deviations, and Sharpe ratios of global minimum variance portfolios consisting the stock market index and one of the two REIT indices based on their dividend payout policies; high-payers and low-payers. Index level portfolios are updated every week while firm level portfolios are updated every four weeks. In Rolling Window Correlation Model, no method is imposed on var-cov matrix while in DCC Model assumes the Dynamic Conditional Correlation Model. Ex-post results use information up until t in portfolio allocation and Ex-ante results use information until $t-1$. Short sales are not allowed.

	Random Walk Model		**DCC Model**	
	Ex-post	**Ex-ante**	**Ex-post**	**Ex-ante**
Panel A1: Portfolios with REIT Indices – Stock + Low REITs				
Expected Return	0.1159	0.1157	0.1159	0.1157
Standard Deviation	0.0022	0.0022	0.0001	0.0001
Sharpe Ratio	52.3090	52.2187	2931.5469	2930.5320
Panel A2: Portfolios with REIT Indices – Stock + High REITs				
Expected Return	0.0495	0.0493	0.0495	0.0493
Standard Deviation	0.0022	0.0022	0.0001	0.0001
Sharpe Ratio	22.4000	22.3100	1272.2300	1270.7300
Panel B1: Portfolios with REIT Firms – Stock + Low REITs				
Expected Return	0.0194	0.0192	0.0124	0.0123
Standard Deviation	0.1605	0.1606	0.1396	0.1391
Sharpe Ratio	0.0917	0.0912	0.0682	0.0677
Panel B2: Portfolios with REIT Firms – Stock + High REITs				
Expected Return	0.0179	0.0178	0.0205	0.0199
Standard Deviation	0.1664	0.1665	0.1326	0.1319
Sharpe Ratio	0.0799	0.0794	0.1087	0.1063

Overall, the table highlights the advantages of using the DCC model and using a sub-group of REITs based on their dividend payouts for constructing global minimum variance portfolios, particularly when dealing with assets like REITs with time-varying correlations.

Mean-variance efficient test statistics and efficient frontiers suggested that high-dividend-paying REITs expand the investment universe by providing extra diversification. The results on portfolio analysis presented Panel B of Tab. 4 confirm this finding when the DCC model is employed by producing higher Sharpe ratios for the portfolio with high REITs.

The portfolio allocation analysis concluded that each sub-groups of REITs provides a different diversification level. The DCC model produces portfolios of lower risk compared with rolling window correlation model. The performance of each model is similar in ex-post and ex-ante optimization. Portfolios with high-dividend-paying REITS offers the highest Sharpe ratios to stock market investors at both index and firm level analysis.

4.3 Time Varying Diversification Benefits Analysis

Using index and firm level data in the previous sections, we found that a portfolio containing high-dividend-paying REITs and the stock market index outperformed one that contained low-dividend-paying REITs. It is imperative to note that these empirical results are based on averages. This study provides a valuable opportunity to examine diversification benefits associated with our sub-groups of REITs over time. For a particular sub-group of REITs to be deemed superior in portfolio optimization, it must consistently outperform the other sub-group. Validating the persistence of diversification advantages of a REIT sub-group over time would further substantiate the practice of classifying REITs based on dividend payout ratios.

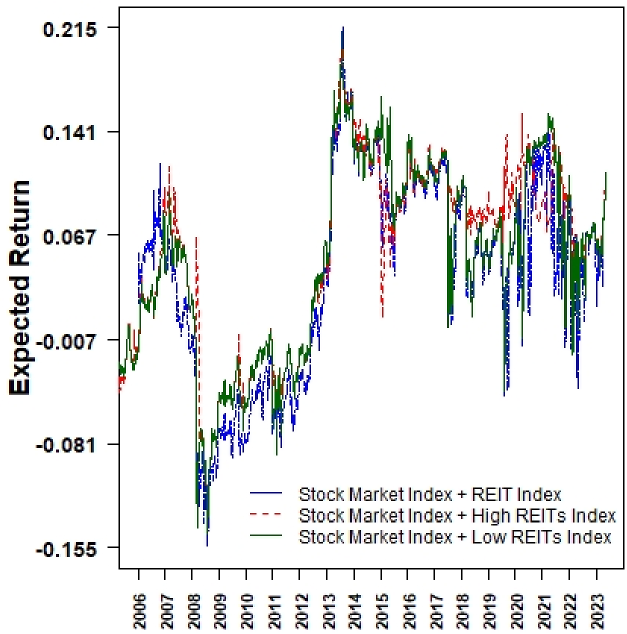

Fig. 6: Index Level Global Minimum Portfolio Ex-ante Time-Varying Expected Returns

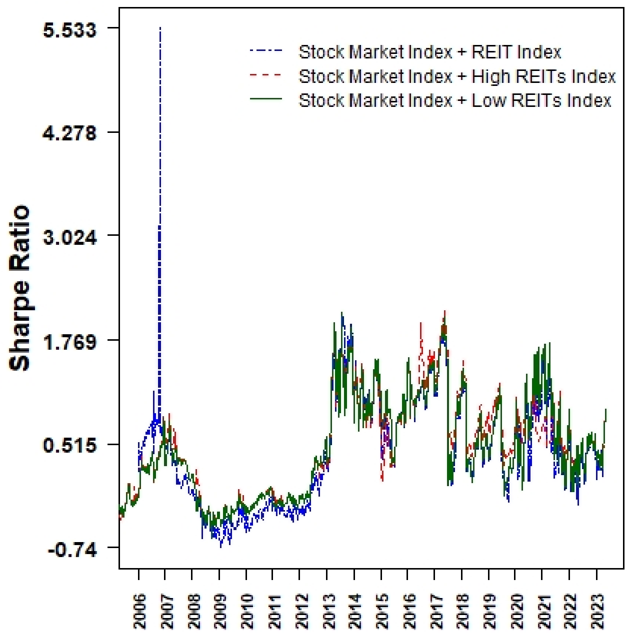

Fig. 7: Index Level Global Minimum Portfolio Ex-ante Time-Varying Sharpe Ratios

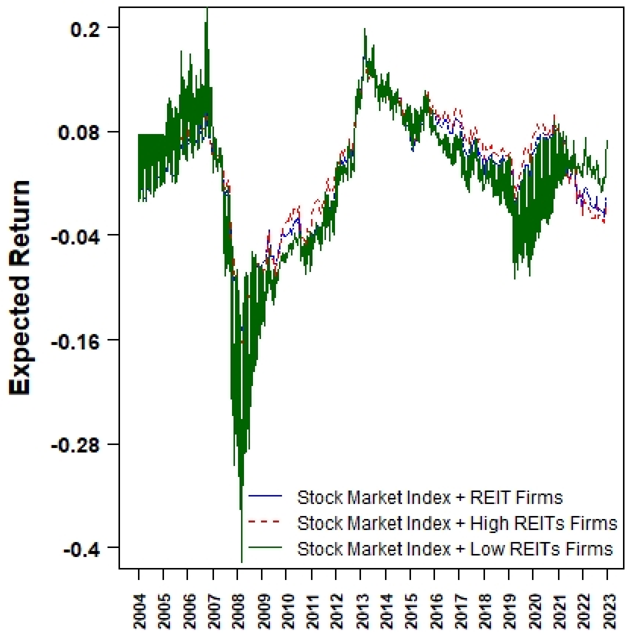

Fig. 8: Firm Level Global Minimum Portfolio Ex-ante Time-Varying Expected Returns

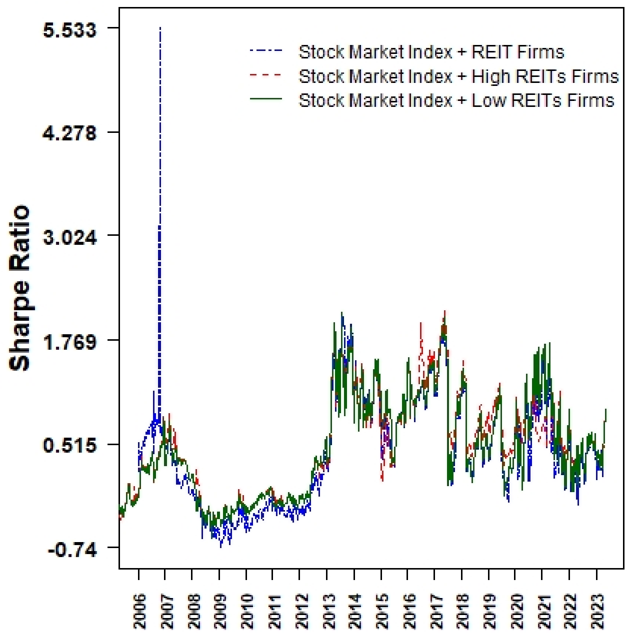

Fig. 9: Firm Level Global Minimum Portfolio Ex-ante Time-Varying Sharpe Ratio

Thus, we now examine the time-varying properties of portfolio optimization. Fig. 2 displays expected returns and Sharpe ratios of the portfolios optimized using ex-ante forecasts of the covariance matrix from the DCC model. Panels A and B display expected returns and Sharpe ratios of portfolios including indices of low- and high-dividend-paying REITs plus the stock market index from January 2005 to December 2022. At the index level portfolio optimization, high-dividend-paying REITs plus the stock market index portfolios have the higher expected returns and Sharpe ratios most of the time, which confirms our results in mean-variance spanning test and portfolio optimization analysis. In the firm-level optimization analysis, as illustrated in Panels C and D, the superior performance of high-dividend-paying REITs is evident. While the differences between portfolios of various REIT sub-groups may not be distinctly observable during certain brief periods, a careful examination reveals that high-dividend-paying REITs consistently deliver higher expected returns and Sharpe ratios during the 2008 financial crisis. Conversely, during the Covid-19 period, low-dividend-paying REITs exhibit higher expected returns and Sharpe ratios, corroborating the findings presented in Panel E of Tab. 2.

Next, we present figures of time-varying expected returns and Sharpe ratios of global minimum variance portfolios at index and firm levels. Forecasts of covariance are from the DCC model. Fig. 6 and 8 report the expected return on the portfolio of the stock market index and grouped REITs indices and firms. Fig. 7 and 9 represent the Sharpe ratios of the portfolio of the stock market index and grouped REITs indices and firms. Grouped REIT indices are weighted average of REITs based on their dividend payout ratio. Low REIT and High REIT represent low-dividend paying and high-dividend paying REITs, respectively.

5 CONCLUSION

The literature places great interest in understanding the diversification benefits and portfolio performance of an actively managed portfolio. Especially so, during a liquidity crisis when the market faces large shocks and investors need diversification the most. The majority of the studies examining REIT diversification potential and REIT performance in portfolio allocation are limited by in-sample analysis or use unrealistic methods such as ex-post covariance matrix estimates. We use two distinct models to empirically study the differential diversification power of REIT sub-groups formed using dividend payout ratios. The performance is measured before, during, and after the global financial crisis in 2008 and during the Covid-19 period to help understand diversification benefits over time.

Using index and firm level data at weekly frequency, we forecast ex-post and ex-ante variance-covariance matrices employing a rolling window correlation and a DCC model to test diversification benefits of REIT sub-groups formed based on dividend payout ratio. We use several methods to study the issue, including a regression-based mean- variance spanning test, mean-variance efficient frontiers, and an out-of-sample minimum variance portfolio allocation practice in ex-ante optimization framework.

The most important finding of the current study is that diversification benefits of the REIT market are affected by the dividend payout ratios of REITs. Not only do REITs expand the investment universe for the stock market index investors and provide more profitable or less risky portfolios, the diversification benefits vary directly according to REIT dividend policy. REITs sub-grouped by their dividend payout ratios offer different levels of diversification. Furthermore, these REIT sub-groups have the capacity to left-shift the efficient frontier of a market portfolio with or without the other sub-group of REITs.

The primary aim is to realistically test the diversification benefits of REITs and the role of dividend policy in diversification by using an out-of-sample portfolio optimization with ex-ante variance-covariance matrix forecasts. In addition to confirming some of the empirical findings in the literature, the current study presents further evidence of the diversification power of REITs and its relationship with dividend policy. The contributions in this study allow new insights to academics, active portfolio managers, as well as REIT market regulators with respect to the relationship between REITs and the stock market and in turn the role of REITs in mixed-asset portfolios.

The inherent illiquidity of the real estate market makes it more suited for long-term investments. However, real estate market securities such as REITs have been developed to provide more liquid and stock-like securities to real estate market investors. Although REITs share similarities with general stocks, they are generally less liquid and the level of illiquidity can vary across different countries. Additionally, the 2008 global financial crisis demonstrated the severity of liquidity risks in the REIT market. As a result, one of the significant challenges faced by the real estate securities market is the need to create more liquid variations of these securities, gain access to more liquid markets such as the digital-securities market, or both.

It is recognized that the lack of liquidity in REITs could contribute to the low correlation between REITs and general stock market indices. However, we believe that any such correlation bias resulting from illiquidity would be uniform across all sub-groups of REIT-stock market index correlation pairs. The primary focus of the paper is to analyze the impact of dividend policy on dynamic correlations using ex-ante variance-covariance matrices based on both a rolling window correlation and a DCC model. This effect would still be present regardless of whether correlations may be downwardly biased or not.

The paper highlights numerous notable aspects, namely its novel methodology for analyzing the diversification advantages of REITs by classifying them according to dividend payout ratios. By utilizing both the Dynamic Conditional Correlation (DCC) model and a rolling window correlation approach, the paper provides a thorough analysis that accurately represents the changing nature of asset correlations throughout time. Adopting this dual-method approach strengthens the reliability of the results and enables a more profound comprehension of how different sub-groups of REITs contribute to diversifying investment portfolios throughout different economic eras, such as the 2008 global financial crisis and the Covid-19 pandemic. Moreover, the utilization of both ex-ante and ex-post optimization frameworks offers a comprehensive evaluation of portfolio performance in practical situations.

Our study complements existing research on REITs, while also pushing the boundaries of current scientific knowledge by focusing on dividend-based sub-groups and their distinct diversification benefits. By utilizing advanced forecasting models, our results highlight the importance of considering time-varying correlations when optimizing REIT-heavy portfolios. It adds new layers of understanding to the role of REITs in multi-asset portfolio optimization, reaffirming established findings.

Nevertheless, the study is not without limitations. An evident limitation is the dependence on past data, which could restrict the relevance of the conclusions to future market situations, particularly considering the fast-changing character of financial markets. Moreover, since the study only examines U.S. REITs, the findings may not be applicable to REITs in other countries subject to distinct legal and market conditions. One further constraint is the possible influence of liquidity limitations on the outcomes, especially during times of market distress. Although this issue is acknowledged, it remains a factor that could influence the observed diversification benefits. Finally, the study's classification of REITs based solely on dividend payout ratios, while innovative, may overlook other significant factors that influence REIT performance and investor behavior.

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