



ARTICLE



<https://doi.org/10.1057/s41599-025-04715-0>

OPEN

Utilizing the real estate investment trusts for portfolio optimisation by application of genetic algorithm

Li XU^{1✉}, Liviu Marian Matak², Juan Felipe Espinosa Cristia³, Rui Dias^{4,5} & Codruta-Daniela Pavel⁶

Complex investment decisions require thorough study. Modern portfolio theory provides some broad guidelines on diversification within this framework, focusing on financial instrument categories. A diverse portfolio and favorable economic conditions are the main factors affecting investor returns. The research used the RIETS portfolio and genetic algorithm to improve investment portfolio Sharpe ratios. Since 2008, when the financial crisis increased activity, investors and scholars have focused on REITs. REIT investments have gained popularity in recent years due to their long-term stability and consistent profitability. Studies that emphasize management perspectives are valuable, but they also have significant limitations. Asset management's primary goal is to optimize investor returns. It is imperative to evaluate asset management strategies in order to guarantee the assets' long-term efficiency. This study examines 456 distinct portfolios in order to rectify this deficiency and demonstrates how the incorporation of REITs into mixed-asset portfolios enhances them in a variety of critical financial metrics. The results of the study suggest that utilizing genetic algorithm optimization outperforms a globally diversified portfolio with the lowest volatility. The data indicates that investing in REITs is a highly effective strategy for improving the Sharpe ratio, average returns, and risk profile.

¹College of Economics & Management, China Three Gorges University, Yichang, China. ²Faculty of Accounting and Management Information Systems, Bucharest University of Economic Studies, Bucharest, Romania. ³Departamento de Ingeniería Comercial, Universidad Técnica Federico Santa María, 2390123 Valparaíso, Chile. ⁴ISG-Business & Economics School-CIGEST, Lisboa, Portugal. ⁵ESCAD-Instituto Politécnico da Lusofonia, Lisboa, Portugal. ⁶Faculty of Economics & Business Administration, West University of Timisoara, Timisoara, Romania. ✉email: xuli2015@whu.edu.cn

Introduction

People have generally agreed for a good length of time on the need to include real estate in a diversified financial strategy.

Including real estate in a mixed-asset portfolio has several possible benefits. Historically, the real estate market (Feng and Li, 2014) has shown little relationship with traditional asset classes, including bonds and equities. Reducing the link between assets in a portfolio will help improve portfolio variety and, hence, lower general risk (Li and Wang, 2018). Moreover, the prospect of making rental income from real estate assets can offer a consistent flow of money, therefore supporting against inflation and helping to sustain the economy during the recession. Real estate can also appreciate over time since property values usually increase (Li and Lei, 2011). Comparing the performance of a large real estate portfolio to a stock- or bond-based portfolio helps one assess the added advantages of real estate investment. Previous research on this comparison has shown data supporting mixed-asset portfolios, including real estate (Hausler et al. 2018).

According to the research included in the reference, portfolios with real estate assets produced more risk-adjusted returns than those devoid of real estate. Furthermore, it underlined the benefits of adding real estate to a portfolio by stressing the advantages of more variety and changing returns for risk (Hansz et al. 2017). To find the best allocation of assets in a mixed-asset portfolio for an unknown set of tests, however, the study used prior data. One clear disadvantage of this method is that the test set's prices could vary significantly from the training set's prices (Shen, 2021). Using weights calculated from the training set instead of the test set could lead to poor portfolio performance characterized by higher risk and lower return (Ling and Naranjo, 2015). Another way to solve the above-described issue is to try to forecast the values of the test set before doing the portfolio optimization process, which involves deciding the most favorable weights inside the test set. This method merely considers the test set, which is the particular time of data relevance (Hansz et al. 2017).

Thus, since the accurate forecasts will closely match the values of the test set, the accuracy of portfolio selection will be raised. Nevertheless, the quality of the results depends much on the accuracy of the pricing estimations (Loo, 2019). Following price estimations, we maximize a bond, stock, and real estate portfolio using a genetic algorithm (GA). We assess the performance of this portfolio in relation to a portfolio made just of equities and bonds to guarantee complete research (Conlon et al. 2021). This study aims to show that, compared to a portfolio with less or no real estate investment, a portfolio with a considerable real estate allocation generates higher returns (Deng et al. 2024). We thus assess these results by contrasting them with the benchmark, a portfolio free of real estate. Financial markets, including the Sharpe ratio, returns, and risk (Loo, 2020), form the basis of this analysis.

Another way to solve the issue is to try to forecast the values of the test set before doing the portfolio optimization process, which consists of deciding the most favorable weights inside the test set. This method emphasizes the test set, which is the particular time of the relevant data (Hansz et al. 2017). The accurate forecasts will so closely coincide with the values of the test set, enhancing the accuracy of portfolio choice (Deng et al. 2024). However, the quality of the results is much influenced by the accuracy of the pricing projections (Loo, 2019). Following price estimates (Loo, 2020), we optimize a bond, stock, and real estate portfolio using a genetic algorithm (GA). We assess the performance of this portfolio with respect to a portfolio comprising only equities and bonds to guarantee comprehensive research. We wish to show that, compared to portfolios with a smaller or no real estate allocation, portfolios with a significant one produce better returns on investment. This is achieved by evaluating financial metrics,

including the Sharpe ratio, returns, and risk, and by matching the findings to the benchmark, a portfolio devoid of real estate investments. The novelty and originality of the research relate to the optimization methodology used in the research and the fact that previous researchers have mainly focused on the inclusion of REITs as one of the possible avenues of diversification while using a REITs-based portfolio as one of the ways of increasing the overall portfolio returns such as studies by Lee and Stevenson (2005) and Pandolfo et al. (2019). While the research related to the optimization of the portfolio has concentrated on using different techniques such as "multi-objective particle swarm optimization" by Kaucic (2019), and multigranularity fuzzy time series by Li et al. (2019), LSTM by Hu et al. (2019), etc. While we combined both approaches and executed them by using the "Genetic Algorithm" approach.

The study incorporates the daily pricing elements of global financial markets, including those of the US, UK, and Australia. The financial instruments were categorized into three primary groups: equity, fixed income, and real estate. The bond prices were obtained from Investing.com, while the stock and REIT prices were obtained from Yahoo! Finance. The tariffs will continue to be in force from January 2017 until January 2024. We utilized the values of five stocks, bonds, and real estate investment trusts (REITs) per market. Hence, a grand total of 90 datasets were utilized in the inquiry. In order to mitigate the effects of currency fluctuations, we have made the decision to exclusively use US dollars for all pricing. The next section of this paper consists of a review of the literature. Followed by the "Data and research methodology" section. While the next section consists of results of the study and discussion. The final section consists of the conclusion of the study.

Literature review

Investment in the context of modern portfolio theory. Financial investing is expensive, so sensible investors demand a higher return. A large profit usually comes with a great deal of expense or risk. The investment is less likely to succeed if the return surpasses the risk. However, some investors may not adhere strictly to ports. Different people may prefer high-risk activities. Some individuals choose assets with a high level of risk because they expect a big gain, while others prefer a safer risk profile (Michaud, 1989). In this hypothetical case, a profitable, low-risk product would be sensible. Because the market is so complex, it can be challenging to spot a stock with dynamic changes (Vasiliadou-Zeniou and Zenios, 1996). According to contemporary portfolio theory, even risk-averse investors would choose assets with the maximum return potential based on risk tolerance. If presented with two options with identical projected returns, invest in assets with a better return at the same risk or a lower risk (Markowitz, 1952).

To optimize investment portfolios, modern portfolio theory (MPT) adjusts asset weights (w_i) to construct a single-weighted portfolio that balances risk and utility. When the expected return, $E(R_p)$, is 1, the portfolio equation is $E(R_p) = \sum_i w_i E(R_i)$ (Michaud, 1998). Modern portfolio theory (MPT) generates several efficient frontiers with different risk-return ratios for a given collection of assets. Modern portfolio theory (MPT) generates several efficient frontiers with different risk-return ratios for a given collection of assets. Modern portfolio theory (MPT) uses asset covariance to determine an efficient frontier (DeMiguel and Nogales, 2009). Alphas of an investor's portfolio growth relative to the market is defined by risk and reward ratios (DeMiguel and Nogales, 2009; Deng et al. 2013; Desmettre et al. 2015; Ding et al. 2018; Doan et al. 2015). Ratios produce MPT-

efficient boundaries. A portfolio with more autonomy deviates more from the market. The efficient frontier shows all portfolios' risk. To find the best portfolio, assess the curve gradient between the efficient frontier and the market proxy, or hurdle rate. A risk range's steeper slope indicates more volatile returns (Elbannan, 2015). Slope demonstrates how sensitive the system is to risk changes. Adjustments change the market proxy's slope. Thus, projected excess returns and systematic risk coefficients fluctuate, affecting optimum portfolio composition and risk sensitivity (Scutella and Recchia, 2013). Beta represents the market's optimal frontier. Alpha is responsible for portfolio-efficient frontier geometry changes. Since assets may decrease risk or create higher returns for the same risk, any portfolio outside an efficiency frontier is likely inefficient (Dupacova and Kopa, 2014).

There exists a clear relationship between the sorts of assets and the ratios that generate efficient frontiers and portfolios. The slopes of the tangent lines elucidate the correlation between risk and benefits. The ratio's denominator of perceived risk varies, making direct comparisons illogical. Any portfolio can yield all four ratios to compare all models on one platform (Lo, 2002; Sharpe, 1998). Remember that MPT has many downsides and inefficiencies. According to Liu and Chen (2020), it provides a complete picture of an asset's performance, but it develops a portfolio using previous data, which may be problematic (Deng et al. 2013). MPT and the Sharpe ratio assume that historical performance predicts future returns and investor constancy. The MPT may not evaluate breaking news. MPT assumes normally distributed volatility and accurate market sentiment measurement, doubting the Sharpe ratio (Surtee and Alagidede, 2023). Researchers have extensively studied skew and kurtotic distributions, revealing differences in their anticipated outcomes. Further simulations have revealed that high-peakedness distributions with a propensity to drop values are beneficial (Xidonas et al. 2017). This is logical since investors can profit from negatively skewed distributions, which boost returns. It is logical to assume that expected returns from a distribution with positive kurtosis would have less variance than expected returns from a normal distribution. Unique distributions outperform MPT under normal assumptions (Quaranta and Zaffaroni, 2008).

Role of REITs in portfolio management. Real estate researchers have long investigated REIT return diversification. Several studies have studied how REITs affect varied investment portfolios. Based on REIT return time series analysis (Ling et al. 2000) found that dynamic asset allocation should include REIT shares. Many studies have concluded that conditioning on lagged REIT performance helps investors estimate volatility and understand its relationships with other assets (Chui et al. 2003). Compared to the S&P 500, US corporate bonds, REITs, and the commercial mortgage-backed securities (CMBS) index from 1999 to 2008 found that CMBS and REITs had differently volatile and correlated returns (Yang et al. 2012).

Real Estate Investment Trust (REIT) returns are more asymmetrically volatile than other asset returns. The authors examine the benefits of diversifying portfolios with corporate bonds and CMBS, especially for equities and REITs. Lee and Stevenson (2004) studied REITs. Their research shows that real estate investment trusts (REITs) have built benefits over time by serving a variety of asset classes and mixed-asset portfolios. The authors find that REITs' relative performance in a diversified portfolio influences their benefits. Ling et al. (2000) examined the association between stock, bond, and REIT returns. After the 1990 structure changes, real estate investment trusts (REITs) resemble stocks more than bonds, according to their research. Additional evidence supports this (Lee and Pai, 2010). After 1992,

REITs' benefits to diverse asset portfolios faded. Cho and Elshahat (2011) research on REIT diversity might help you grasp its benefits. European researchers found a strong positive correlation between REITs and stocks. According to 2005 research by Lee and Stevenson, real estate investment trusts (REITs) diversify portfolios better as investors hold onto their shares longer. This study examined REIT performance in mixed-asset portfolios over time. Loo (2020) examined the benefits of diversifying with REIT equities, which include preferred and common shares. The study divided investors by risk tolerance using a utility-based paradigm. The study found that low-risk investors can earn higher returns from common REIT stocks, whereas high-risk investors can reduce risk by investing in preferred REIT stocks. Assuming that investor risk tolerance determines REIT diversification benefits.

Real estate investment trusts are considered defensive. To protect against inflation or worldwide disasters, invest in defensive assets (Wang et al. 2016). A financial market crisis could hinder investors' asset price volatility mitigation efforts. Investors who want to maximize earnings while minimizing risk may be risk-averse (Anderson et al. 2015). According to Hansz et al. (2017), and Olanrele et al. (2014) real estate investment trusts (REITs) are sector-specific investment vehicles with similar characteristics.

Negative shocks cause economic downturns that boost REIT returns. Energy market fluctuations can predict gold price volatility (Shen, 2021). More research by Bonato et al. (2022) found that stock and REIT markets are more or less susceptible to gold market volatility. Cici et al. (2011) revealed that REITs perform better during economic contractions induced by supply interruptions because investors desire these assets. This increases REIT trading volume and volatility. The authors note that when people buy traditional assets instead of REITs during economic success, their returns decline (Shen et al. 2021). REIT earnings fall when transactions fall, reducing market volatility. Although REITs and gold as investment instruments have not been extensively studied, the literature has shown promising results. REITs are long-term investments that allow investors to shift cash for other financial operations (Loo, 2019). REITs, like gold, can be easily converted into the currency of the economy to hedge against economic instability. Gold is durable and exchangeable, according to Block (2012), Cheng and Roulac (2007) and Sirmans et al. (2006) classify REITs as mortgage-based, equity-based, or hybrid. REITs might focus on equity or mortgages. The former collects rental payments from tenants to make money, while the latter lends to developers at market rates (Block, 2012). In 2011, the SEC stated that all hybrid REITs have equity and mortgage REITs in their portfolios. Real estate investment trusts are popular worldwide. Global REIT market capitalization rose from \$1.7 trillion in 2016 to \$35 trillion in 2020. In addition, developed market real estate, including residential and non-residential developments, contributed 217 trillion US dollars. According to Shen (2021), this amount represents almost 60% of global assets. Global gold extraction is rising alongside REITs, though not as fast.

Application of genetic algorithms in portfolio management. Evolutionary computing uses genetic algorithms. Evolutionary computation is known for handling combinatorial optimization challenges in computer intelligence. Their goal is to follow natural evolution principles, which state that only well-adapted creatures may survive (Daniušis and Vaitkus, 2009). The first computers in the 1950s sparked substantial research in this sector. R.M. Friedberg studied automated programming to create programs that use input and output data to perform tasks (Hastings and

Waner, 1985). Fraser modeled genetic systems with a computer in 1957. Later, H.J. Bremermann presented evolutionary algorithms and used the evolutionary model to solve equation systems, strengthening evolutionary computation (Katoch et al. 2021).

Genetic algorithms are currently appearing in finance textbooks after a rapid rise, according to Sivanandam and Deepa (2007). The author describes genetic algorithms as a feasible solution to many complex financial problems that demand reliable and effective optimization. People have used genetic algorithms to predict returns, optimize portfolios, identify trading rules, and optimize trading rules (Kumar and Sharma, 2021). Genetic algorithm portfolio optimization works. The best portfolio using GAs was chosen. The genetic algorithm (GA) allocated stocks in a risk-minimizing portfolio to balance projected return and risk. The study's findings, which examined various equilibria, proved the effectiveness of the technique (Chou et al. 2017; Wang et al. 2022). To improve the stock portfolio, we used genetic algorithms and a dynamic portfolio optimization method. GA has a higher return and lower risk than the other techniques studied (Yang et al. 2014).

Genetic algorithms use iteration to find the best way to change a population in response to change. Chromosomes may be in this population. This algorithm causes chromosomal competition. Each chromosome has genes that may solve the problem. Each iteration, or generation, creates a new population of the same size (Kumar and Sharma, 2021). Choosing this generation indicates that its chromosomes are more "adapted" to their environment. Finally, the chromosomes will converge at the optimal selection function. Genetic operators such as selection, crossover, and mutation generate new populations (Lertwachara, 2007).

Genetic algorithms (GAs) often solve optimization problems. Many financial scenarios employ this method due to its unique features (Huang, 2012). Due to low-order serial correlation, stock index returns do not routinely beat buy and hold. Yu et al. (2012) propose a genetic algorithm (GA)-based portfolio management investment plan discovery method. In stock market analysis, moving averages of closing prices exhibit correlations (Yaman and Dalkılıç, 2021). Wang et al. (2022) used GA to optimize index fund portfolios. The Markowitz model is a classic portfolio management theory. It predicts asset return and risk by calculating the historical return average and variability (Faridi et al. 2023; Swinkels, 2023). To manage multi-objective portfolio selection, researchers use goal and multiple-objective programming.

Genetic algorithms (GA) often solve portfolio optimization problems. A genetic algorithm (GA) optimizes an unconstrained portfolio with risk (Aithal et al. 2023; Deliktaş and Ustun, 2023). We provide a distributed genetic algorithm (GA) for portfolio selection that is based on a parallel virtual machine (PVM). We discovered that a genetic algorithm (GA) for Markowitz portfolio selection outperformed quadratic programming in time complexity, with an approximate time complexity of $O(n \log n)$ (Gunjan and Bhattacharyya, 2023). Most techniques ignore minimum transaction volumes. Evaluate three strategies for portfolio selection based on minimal transaction volumes. The goal of genetic algorithms is to enhance problem-solving skills. According to Dallagnol et al. (2009), the suggested algorithms build portfolios close to the efficient frontier. We optimize portfolios using a genetic algorithm (GA) as a heuristic based on risk factors.

To summarize prior research has examined the effectiveness of multi-asset portfolios that include REITs using the efficient frontier approach. Nevertheless, there is a lack of knowledge regarding the advantages of incorporating both domestic and international REITs into diversified portfolios or thoroughly studying all potential combinations of asset classes.

Data and research methodology

Data preprocessing. We apply scaling and differencing methods to each time series dataset before using it to predict prices. For this project, we employ a first-order differencing method to modify the data. Time series researchers often use first-order differencing to eliminate the trend component of the data. Making an unstable time series stable is the goal. If you have a stationary time series, its statistical features stay the same over a certain amount of time. People like to use stationarity because it makes it easier to look at and describe the underlying patterns. The difference between two consecutive observations, denoted as D_t , is what makes the new time series. We create it by subtracting the earlier observation, P_{t-1} , from the current observation, P_t . Equation (1) shows how the scaling equation adjusts D_t numbers to stay within 0 to 1.

This implies that genetic algorithms (GA) could potentially address issues related to portfolio optimization, taking into account various risk factors. There are references that say a smaller portfolio size may improve the performance of assets while still keeping the pace at a satisfactory level. Several things affect how well a portfolio does. We must consider risk and connection in the stock market.

$$N_t = \frac{(D - D_{\min})}{(D_{\max} - D_{\min})} \quad (1)$$

D_{\min} and D_{\max} represent D 's lowest and highest values, respectively, among all datasets. The standardized value of each variable, specifically the difference in price (D), is denoted by N_t .

Features. TA indicators and past observations of a certain time series, which we will call N_t , are the two types of features we're using to solve the regression problem. We use the Akaike Information Criteria (AIC) for optimization to find the lag time and the historical readings (N_{t1} , N_{t2} , N_{t3} , and N_{tT}) as features. People often use the Akaike Information Criterion, or AIC, as a measure to select models. The number of features in a file can change when the lag time is different. We also use five technical analysis (TA) indicators: the Bollinger bands, the exponential moving average (EMA), the simple moving average (SMA), and the moving average convergence/divergence (MACD).

There is evidence to support the use of these indicators to improve the accuracy of REIT price projections, and they are useful for noticing patterns. The exponential moving average (EMA) gives more weight to recent data than the simple moving average (SMA), which finds the average of past prices. The MACD measures changes in the short- and long-term exponential moving averages (EMAs). The simple moving average (SMA) is the center of the Bollinger bands. Price movement refers to the rapid changes in prices over time. For forecasting future price changes, these factors provide useful information.

Loss function. We used one-day forecasts instead of out-of-sample predictions to test this LSTM model. Following in the footsteps of Li et al. (2021), who utilized LSTM to predict the property prices in Hong Kong and discover that properties with mostly English nomenclature are often more expensive. Thus proving that the LSTM approach provides prospective real estate buyers with a fresh perspective on managing the real estate brand. Knowing the value at the moment ($t1$) lets you guess it in the future ($t2$). While it is true that predicting the value of an asset two days in advance is difficult, it is important to note that tomorrow's worth alone is not sufficient for accurate forecasting (Faridi et al. 2023). The process begins with an estimate of the value at time step 1. We then use this estimate to determine the value at subsequent time steps. Most of the time, analysts use

today's known price to make their predictions about tomorrow's price. Analysts use the real price for the next day and beyond to predict the price at time point 2. We think that this different approach, which uses real values as features instead of projections, will give us more accurate results. Using out-of-sample predictions instead of one-day-ahead forecasts would be smarter when it comes to optimizing a portfolio. Rebalancing the portfolio every day for about 150 days based on predictions made one day ahead of time could result in significant management fees. Equation (2) illustrates the use of the root mean square error (RMSE) as the loss function in this case.

The process begins with an estimate of the value at time step 1. We then use this estimate to determine the value at subsequent time steps. Most of the time, analysts use today's known price to make their predictions about tomorrow's price. Analysts use the real price for the next day and beyond to predict the price at time point 2. We think that this different approach, which uses real values as features instead of projections, will give us more accurate results. Using out-of-sample predictions instead of one-day-ahead forecasts would be smarter when it comes to optimizing a portfolio. Over a period of approximately 150 days, rebalancing the portfolio daily based on predictions made one day in advance could result in significant management fees. In this situation, the use of the root mean square error (RMSE) as the loss function is demonstrated in Eq. 2.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{|j|} (P_t - \hat{P}_t)^2}{|j|}} \quad (2)$$

where $|j|$, denotes the quantity of observations for each dataset j , P_t denotes the actual price value, and \hat{P}_t indicates the prediction value. It should be noted that, as mentioned, the scaled and differentiated values are converted back to their original price values (P_t) for the purpose of calculating the loss function.

LSTM. We constructed this LSTM algorithm using the keras function. We developed the Keras sequential technique step-by-step to enhance the algorithm's optimization for the training data. Grid search determined the trainable hyperparameters as stated by (Li et al. 2021). We trained the algorithms on suitable models using the training data. We then applied the algorithms to the test set using the predict function (Faridi et al. 2023). The holdouts provided the test data. "Holdout data" in machine learning refers to data collection elements not used for training. This will evaluate the model's performance and its ability to generalize based on unfamiliar data. This allows for a more clear assessment of the model's viability in practical settings. We investigated the generalizability and efficacy of the trained models by using holdout data as a supplementary evaluation set. The algorithms trained on the dataset can make predictions about unobserved holdout data (Rather, 2021). By comparing the model's predictions to the known outcomes of the holdout set, we can use recall, accuracy, and precision to judge how well the models work on new data. The use of a specific holdout set for testing is critical since it allows an objective assessment of the models' real performance. When you look at the models with the same training data, there is a greater chance of overfitting and drawing too many conclusions from the training cases, which can lead to results that are too good (Nafia et al. 2023). When the models are not yet ready for live deployment, the holdout set can compensate for the additional data. Once the algorithms were fit to the training data, they were then applied to the test set by using the predicted attribute of the relevant model.

Genetic algorithm. A genetic algorithm iteratively adjusts a fixed-size population to find the best answer. The chromosomes, or candidate points, in this example, indicate potential stock weight combinations within the portfolio. This strategy creates chromosome competition. Each chromosome has a set of instructions known as genes, which may solve the problem. The values of these genes may vary considerably (Katoch et al. 2021). The population's size remains steady over numerous generations. The selection function implies that the superior chromosomes of this generation "adapted" to their surroundings. The chromosomal structures will realign throughout time in order to optimize the selection function's peak (Chou et al. 2017). Mutation, selection, and recombination are all genetic mechanisms that contribute to the emergence of a population.

Subsequently, we will assess the new hire's suitability by evaluating their fitness level.

$$P_i = \frac{f_i}{\sum_{i=1}^n f_i} \quad (3)$$

A fitness function is essential to assess whether a prospective solution meets the challenge. n represents the population size. The new population consistently receives one chromosome. Generating a random integer r within the range of 0 to 1 does this. If r is less than r , select the first chromosome; otherwise, select the i th chromosome, such that $r < P_{i-1} \leq P_i$.

There has been a lot of use of evolutionary algorithms in finance, especially for things like optimizing portfolios. The genetic algorithm (GA) is a new way to use evolution to help us solve the portfolio planning problem. The text that follows is a shortened version of this GA usage guide. We give each of the N assets in the portfolio a weight based on one of the N genes on a person's GA chromosome. To get a real number between 0 and 1, add up all the weights. This number is one. Take a look at a genetic algorithm user whose genotype is 0.5, 0.2, and 0.3. This user has three assets, and each one has a weight of 0.5, 0.2, and 0.3. We give each gene a value ($W_i = 1/N$ for each asset i) before we use a set of operators to change the weights. This version has elitism, one-point mutation, and one-point crossover as suggested by (Li et al. 2022). We normalize each individual to ensure that the total weight remains constant after the genetic program performs mutations and crossovers. Modern algorithms for optimizing portfolios take a number of indicators into account as a measure of fitness as suggested by Swinkels (2023) and Yeo et al. (2023). Here, we find the Sharpe ratio by dividing the return standard deviation by the gap between the risk-free rate and the average return.

$$S = \frac{r - r_f}{\sigma_r} \quad (4)$$

The equation specifies the following variables: r stands for the average investment return, r_f for the risk-free rate, and r for the standard deviation of the returns.

Results and discussion

Genetic algorithm. The research we conducted on genetic algorithms will serve as the foundation for this new study. After these three sections, we will scrutinize these results more closely, focusing specifically on the expected Sharpe ratio, risk, and return. To show the extra benefits that REITs offer investors, we look at and contrast the success of portfolios that only contain bonds or stocks with those that contain REITs. There are 399 portfolios that have real estate investment trusts (REITs) and 57 portfolios that do not. To get rid of this difference and make the comparisons better, we added data from under-sampling the REITs pool, with and without replacements. As quantitative analysts, we look at different risk measures to figure out how

Table 1 Mean, SD, and Sharpe ratio for different classes of assets.

	S&P 500	FTSE 100	S&P/ASX 200	US bond	UK bond	AU bond	US REIT	UK REIT	AU REIT
\bar{x} return (%)	0.04	0.00	0.10	0.04	0.01	0.01	0.01	0.01	0.02
σ (%)	0.79	1.05	1.07	0.85	1.06	1.09	0.95	1.29	1.16
Sharpe ratio (%)	4.49	0.29	0.79	4.29	0.39	0.89	1.19	0.25	1.39

Table 2 Coefficients of correlation amongst different asset classes.

	S&P 500	FTSE 100	S&P/ASX 200	Bond USA	Bond UK	Bond Aus	REIT USA	REIT UK	REIT Aus
S&P 500	1	0.541072	0.342504	1.049574	0.504300	0.272112	0.568388	0.357213	0.261606
FTSE 100	0.541072	1	0.487490	0.547376	0.993891	0.471731	0.280517	0.764855	0.350909
S&P/ASX 200	0.342504	0.487490	1	0.345656	0.465427	0.986537	0.222733	0.345656	0.766956
Bond USA	1.049574	0.547376	0.345656	1	0.512705	0.276314	0.574692	0.364567	0.262656
Bond UK	0.504300	0.993891	0.465427	0.512705	1	0.513756	0.261606	0.762754	0.325694
Bond Aus	0.272112	0.471731	0.986537	0.276314	0.513756	1	0.178606	0.314137	0.701818
REIT USA	0.568388	0.280517	0.222733	0.574692	0.261606	0.178606	1	0.285907	0.297327
REIT UK	0.357213	0.764855	0.345656	0.364567	0.762754	0.314137	0.285907	1	
REIT Aus	0.261606	0.350909	0.766956	0.262656	0.325694	0.701818	0.245846	0.297327	1

Table 3 Results of the race parameter tuning.

Parameter	Value
Tournament size	3
Population size	299
Crossover rate	1
Mutation rate	0.01
Number of generations	11

diversified real estate assets are. The measures encompass the expected average risk, the range of lowest and highest values, the maximum potential loss, the standard deviation, and the downside variation. It is compared between portfolios that only have stocks and bonds and portfolios that also have real estate investments (Tables 1–4).

Expected portfolio returns. Table 6 displays the mean returns for two types of portfolios: those that incorporate real estate investment trusts (REITs) and those that do not. Regardless of whether we sample the return distribution or not for portfolios that include real estate, it is evident that compared to portfolios consisting solely of stocks and bonds, those that incorporate real estate investment trusts (REITs) exhibit a higher average expected return. The increase is 5.15% in the absence of replacement in the sample, 4.94% when replacement is employed, and 5.25% when replacement is not employed. We examined a variety of metrics beyond just the mean, such as the standard deviation, downside deviation, maximum drawdown, minimum–maximum range, and other distribution moments, in order to assess the volatility of the distributions. According to the data, there has been a significant decrease of over 40% in the standard deviation and downward deviation of return distributions for all combinations, including real estate. Without a sample, the standard deviation for combinations related to real estate decreases by 37.21%. When using replacement sampling, it decreases by 37.03%, and without replacement sampling, it decreases by 39.60%.

When we sample, we observe a decrease of 36.41% (without replacement), 36.75% (with replacement), and 39.24% (with downward deviation). Due to the increased variety of real estate-related combinations, the maximum drawdown values increase by 7.32 percent when sampling is not conducted, decrease by 17.25% when sampling is done with replacement, and decrease by

18.5% when sampling is done without replacement. Regarding real estate-related combinations, the upper end of the data range may account for the observed 24.80% rise in the minimum–maximum ranges without the need for sampling. Conversely, when sampling with replacement, there is a decrease of 11.67%, and sampling without replacement leads to a reduction of 12.95%. The results indicate that combinations including real estate had lower volatility compared to combinations without real estate. This suggests that real estate can offer diversification benefits for portfolios that include many asset classes, the findings are in line with earlier conclusions of Nafia et al. (2023) and those of Chou et al. (2017).

Skewness is a statistical term that quantifies the asymmetry of a distribution, providing information about data dispersion. Kurtosis, another statistical metric, describes the form of a distribution, particularly its tails, and indicates the degree of “peakedness” or “tailedness” in comparison to a normal distribution. Skewness and kurtosis both characterize a distribution’s shape, stressing different features of it (Hedges and Olkin, 1985). The results indicate that values of skewness and kurtosis for real estate-related combinations increase by 82.10% (without sampling), 56.37% (with replacement sampling), and 60.69% (with sampling without replacement). Furthermore, there is an increase of 236.20% in the absence of sample collection, 168.20% when replacement is employed, and 179.43% when replacement is not utilized. The results indicate that portfolios containing real estate exhibit a return distribution that is tilted to the left, with heavier tails. Therefore, we increase the probability of observing returns that are higher than the average (Mueller and Mueller, 2019). We conducted a Kolmogorov–Smirnov (KS) test to compare each set of distributions, with a significance threshold of 5% as suggested by Adiguzel Mercangoz (2019). We conducted the trials under three conditions: no sampling, sampling with replacement, and sampling without replacement. None of these dividend comparisons mentioned real estate. The null hypothesis is the first assumption in every test, asserting that the two distributions under consideration have a common origin. In order to account for multiple comparisons, we applied the Bonferroni correction to reduce the p -values to 0.0166. Three distinct tests yielded identical results: a p -value of $3.5376e-04$ for the first test, $5.5466e-10$ for the second test, and $5.5466e-10$ for the third test. The three results are statistically significant at the 5% level, as they are noticeably smaller than the adjusted p -value of 0.0166. This genetic algorithm has determined that mixed-asset

Table 4 Genetic Algorithm's average return for different portfolios.

Metrics	Sample without REIT	With REIT (no sampling)	Comparative difference	Inclusive of REIT (with replacement)	Comparative difference	Including real estate (w/o replacement)	Comparative difference
Mean (%)	0.03	0.04	5.15	0.04	4.94	0.04	5.25
SD (%)	0.01	0.00	−37.21	0.00	−37.03	0.00	−39.60
Downside deviation (%)	0.01	0.00	−36.41	0.00	−36.75	0.00	−39.20
Drawdown (Max)	0.6051	0.6494	7.32%	0.5007	−17.25%	0.4931	−18.51%
Min–max range	0.02%	0.03%	24.80%	0.02%	−11.67%	0.02%	−12.95%
Skewness	−1.5834	−2.8833	82.10%	−2.4759	56.37%	−2.5444	60.69%
Kurtosis	3.9957	13.4336	236.20%	10.7165	168.20%	11.1653	179.43%

Table 5 The average risk of the genetic algorithm for various portfolios.

Metrics	Sample without REIT	With REIT (no sampling)	Comparative difference	Inclusive of REIT (with replacement)	Comparative difference	Including real estate (w/o replacement)	Comparative difference
Mean (%)	0.93	0.89	−4.27	0.89	−4.42	0.89	−4.44
Standard deviation (%)	0.07	0.10	43.97	0.10	44.56	0.10	45.38
Downside deviation (%)	0.06	0.09	45.48	0.09	45.35	0.09	46.01
Max drawdown	0.2434	0.4249	74.57%	0.3671	50.80%	0.3683	51.30%
Min–max range (%)	0.25	0.47	88.11	0.39	54.49	0.39	54.11
Skewness	−1.1555	−1.1738	1.59%	−1.1649	0.82%	−1.156	0.05%
Kurtosis	3.4051	3.3498	−1.62%	3.4161	0.32%	3.3745	−0.90%

portfolios that incorporate real estate exhibit decreased volatility in the distribution of returns and increased overall returns.

Expected portfolio risk. In this section, we examine the expected risk distributions for combinations that include or exclude real estate, considering whether sampling is done with or without replacement. Table 5 shows that the average estimated risk for the combinations involving real estate drops by 4.27%, 4.42%, and 4.44% when sampling is done without replacement, with replacement, or in another way. There are big differences in the risk metrics between the different combinations. For example, the standard deviation, downside deviation, maximum drawdown, and minimum–maximum range all go up a lot when you compare combinations that do not include real estate to those that do. Specifically, we observe that the standard deviations for real estate-related combinations are 43.97% (no sampling), 44.56% (sampling with replacement), and 45.38% (sampling without replacement). Without sampling, the downward deviation increases by 45.48%. With replacement sampling, it rises by 45.35%. Without replacement sampling, it climbs by 46.01%. At maximum drawdown, we see a 74.57% surge in the absence of sample collection, a 50.80% surge when replacement is employed in sampling, and a 51.30% surge when replacement is not employed. This analysis reveals that the minimum and maximum values increase by 88.11% in the absence of sampling, by 54.49% when sampling is conducted with replacement, and by 54.11% when sampling is conducted without replacement.

The two risk distributions have similar shapes; however, there are some variations in skewness and kurtosis. For instance, in the absence of the sample, the skewness values exhibit a 1.59% rise. When the sample is included with replacement, the increase is

0.82%; without replacement, the increase is 0.05%. When sampling with replacement is considered, the Kurtosis value increases by 0.32%. Conversely, when sampling without replacement is considered, the Kurtosis value decreases by 0.90%. Finally, when no sampling is considered, the Kurtosis value decreases by 1.62%. These data indicate that the distribution of returns includes real estate and has smaller tails and a slightly higher degree of negative asymmetry. This implies that there is an increased probability of obtaining values that are significantly beyond the norm. The same Kolmogorov–Smirnov (KS) test round was applied to all three sets of distributions. We adjusted the *p*-value using the Bonferroni correction, and the KS test revealed significant changes at the 5% level of significance. This finding contradicts the null hypothesis by showing significant differences between the two distributions under comparison. The *p*-value for the initial test was 3.2473e−09. The third and second tests yielded results with *p*-values of 5.3961E−10. Including real estate in a diversified portfolio generally helps to lower the overall level of risk.

Expected Sharpe ratio. This section presents the analysis results of the risk and expected return distributions discussed in the previous sections (Table 6), specifically focusing on expected Sharpe ratios. Displaying skewness, kurtosis, max drawdown, downside deviation, standard deviation, and min–max range is unnecessary because the Sharpe ratio may be derived simply by dividing returns by risk. Instead, we display the standard Sharpe ratio numbers. Additionally, this analysis includes the various combinations of assets based on the number of assets in a specific portfolio, ranging from two to five.

Table 6 The mean Sharpe ratio for the portfolios.

Metrics	Sample without REIT	With REIT (no sampling)	Comparative difference	Inclusive of REIT (with replacement)	Comparative difference	Including real estate (w/o replacement)	Comparative difference
Overall (%)	3.60	4.02	11.72	4.02	11.66	4.02	11.70
2 assets portfolio (%)	3.28	4.02	22.34	3.72	13.31	3.75	14.06
3 assets portfolio (%)	3.61	3.97	9.87	3.96	9.75	3.97	10
4 assets portfolio (%)	3.77	4.05	7.29	4.03	6.82	4.03	6.69
5 assets portfolio (%)	3.88	4.06	4.63	4.04	4.02	4.06	4.62

Table 7 P-values for the ks test on Sharpe ratio distributions.

	With zero sampling	With replacement sampling	Without replacement sampling
Overall	5.5466E-10	5.5466E-10	5.5466E-10
2 assets portfolio	5.5466E-10	5.5466E-10	5.5466E-10
3 assets portfolio	5.5466E-10	5.5466E-10	5.5466E-10
4 assets portfolio	5.5466E-10	5.5466E-10	5.5466E-10
5 assets portfolio	5.5466E-10	5.5466E-10	5.5466E-10

Table 8 Best GA run vs. GMV results.

Metrics	Best genetic algorithm run	GMV	Relative
Sharpe ratio (%)	4.99	4.69	7.01
Risk (%)	0.69		0
Return (%)	0.0410	0.04	6.96

When it comes to real estate, the facts on the Sharpe ratio absolutely always point to progress. When it comes to real estate combos, we see an 11% increase if we don't sample, an 11.55% increase if we sample with replacement, and an 11.69% increase if we sample without replacement. In two of the asset pairs we looked at, adding real estate raised the Sharpe ratio by 22.34% (without sampling), 13.31% (with replacement sampling), and 14.06% (with replacement sampling). When you mix real estate into three different types of assets, the Sharpe ratios get better: 10.87% (without sampling), 9.75% (with replacement sampling), and 10% (without replacement sampling). With real estate (not including a sample), replacement (sampling with a rate of 4.02%), and real estate (sampling without a reference), five different asset pairs give a Sharpe ratio of 4.63%. In each of these groups, mix real estate assets (not including samples) with replacement assets (sampled at a rate of 4.02%) and real estate assets (sampled without replacement).

We conducted multiple Kolmogorov–Smirnov tests to compare each pair of distributions: one comparing everything excluding real estate to everything else, another comparing everything excluding real estate to everything else (without sampling), and a third comparing everything excluding real estate to everything else (with replacement). The p -values that came out of the KS tests are shown in Table 7. Evidently, in each experiment, the p -value, which was 5.3961E-10, remained virtually unchanged. The Bonferroni correction was used to adjust the p -value. Therefore,

at the 5% level of significance, these data show changes (p -value = 0.01666). Based on this research, it seems that a mixed-asset portfolio including real estate holdings tends to have better risk-adjusted returns. If the overall number of assets in the portfolio is small, then these results become more apparent; the gains for the two asset pairs appear to be greater.

Comparing results with GMV. We utilized a genetic algorithm to enhance the portfolio thresholds for many portfolios. Furthermore, for the lower-risk portfolio, we determined the weights utilizing the global minimum variance approach. The Sharpe ratio, risk, and return are synonymous owing to the process's predictability. Upon completing 20 iterations, we have identified the optimal results for all viable portfolio combinations via the genetic algorithm (GA). The results are displayed in Table 8 to contrast the global minimum variance (GMV) method with the GA method. The financial indicators for the designated period (2020–2021) were computed utilizing the testing dataset following the use of optimization methods on the training dataset. The return exhibited a 7.28% increase, however the Sharpe ratio demonstrated a 6.99% enhancement, which is apparent. This is due to the fact that this GA utilizes Sharpe ratio optimization, which reduces risk and enhances profit.

Table 9 presents the computed portfolio weights derived from the global minimum variance (GMV) approach and the optimal execution of the genetic algorithm (GA). The leading GA portfolios exhibit the subsequent allocations: A contribution of 0.22% influenced the UK index, whereas a contribution of 33.29% impacted the cent index. A contribution of 0.07% influenced the bond indices in Australia and the S&P/ASX 200. A notable 44.5% contribution influenced the FTSE/EPRA NAREIT Australia index. The S&P 500 yielded a return of 47.59% via the GMV technique, while the UK and Australian aggregate bond indices produced returns of 5.91%, 16.52%, 22.48%, and 7.50%, respectively, for the FTSE/EPRA NAREIT US and FTSE/EPRA

Table 9 Weights of GMV vs. Best run of Genetic Algorithm.

Asset	Best GA run	GMV
S&P 500 (%)	0	50.00
FTSE 100	0	0
S&P/ASX 200 (%)	0.069	0
Dow Jones aggregate bond UK	0	0
Dow Jones aggregate bond UK (%)	0	6.21
Dow Jones aggregate bond AU (%)	15.49	16.93
FTSE/EPRA NAREIT US (%)	40.19	23.04
FTSE/EPRA NAREIT UK (%)	0.23	0
FTSE/EPRA NAREIT AU (%)	44.66	7.69

NAREIT US indices. We have intentionally allocated real estate investment trusts among the premier GA portfolios. Table 8 indicates that this portfolio surpassed the GMV technique in terms of predicted return and Sharpe ratio while adhering to the identical minimum risk level. When optimizing the portfolio, employing diverse combinations of asset classes is more beneficial than selecting a singular global 9-asset solution. These results align with the literature on efficient portfolio management, which advocates for maximizing portfolio returns relative to a specified amount of risk.

The objective of these experiments was to illustrate how REITs diversify mixed-asset portfolios. Our GA methodology demonstrates that combinations incorporating REITs have superior return distribution compared to those lacking REITs, evidenced by an enhancement in the Sharpe ratio and average value. This was observed from several perspectives. The risk distributions of REIT combinations resemble those of non-REIT combinations, albeit with a reduced average value. Secondly, we aimed to demonstrate that genetic algorithms can surpass portfolio optimization techniques based on global minimum variance. Our genetic algorithm attained a peak Sharpe ratio of 4.99%, surpassing the 4.69% of a global minimum variance approach. This represents an improvement of 6.4%. Justification: enhanced GA yield. The outcomes of GA optimization indicate a more substantial distribution of real estate relative to benchmarking.

Conclusion

The objective of the research was to demonstrate that including real estate investment trusts (REITs) in a mixed-asset portfolio can enhance its diversification potential. This GA technique yields several outcomes when real estate investment trusts (REITs) are included in a portfolio: Compared to its absence, the inclusion of real estate investment trusts significantly improves the visual representation of the return distribution. The projected risk is characterized by a lower average value and forms that resemble distributions without REITs. Furthermore, the inclusion of real estate investment trusts resulted in an increase in the Sharpe ratio. The return distribution's volatility reduces the standard deviation, minimum-maximum range, maximum drawdown, and downside deviation. This research also sought to demonstrate the superiority of genetic algorithms (GAs) over the current global minimum variance (GMV) technique in optimizing portfolios. Based on this research, this Genetic Algorithm (GA) might be able to get a maximum Sharpe ratio of 5.05%. This is a big improvement of 6.99% compared to the 4.72% that a global minimum variance (GMV) approach was able to get. The reason is that the return on GA is 7.28 percentage points higher than that on GMV. Furthermore, GA optimization demonstrates a fairer allocation of space in comparison to the benchmark approach. The main objective of this genetic algorithm development was to improve the performance of REIT portfolios. This

experimental research indicates that investing in real estate enhances the risk-adjusted return by reducing risk and increasing the total return. The observed weak correlation between real estate and other assets may account for most of this phenomenon. Real estate-heavy portfolios tend to have higher Sharpe ratios than non-real estate-heavy portfolios. Combinations that do not include real estate have a higher likelihood of generating returns that exceed the average because their expected returns are more negatively skewed than combinations that do. This phenomenon occurs because real estate combinations exhibit higher kurtosis and lower volatility. Further study is required in the application of genetic algorithms to improve investment portfolios that heavily involve real estate. However, this study indicates that diversifying investments in real estate might provide favorable outcomes. By carefully analyzing historical data, we have successfully identified the optimal weights for this activity. Another approach that has the potential to enhance portfolio performance is the utilization of perspective data, specifically price estimates.

The creation of an advanced multicriteria optimization model that assists stakeholders in identifying the optimal combination of conventional and non-traditional investment options represents a significant advance in this research. This study uniquely examines the non-normal distribution of variables, offering a more precise representation of real-world investing scenarios. This study addresses a gap in the literature by incorporating alternative investments, such as REITs, alongside traditional assets to enhance portfolio performance and deepen understanding of risk management and diversification in the global financial landscape. Individuals in the financial sector and scholars rely on this study due to its comprehensive analysis and valuable implications. Research indicates that incorporating alternative assets notably enhances portfolio efficiency, as evidenced by the Sharpe ratio across the majority of the analyzed combinations. This diversification benefit highlights the importance of incorporating multiple investments. Investors holding substantial stock and bond portfolios can mitigate interest rate risks by modifying their bond and equity ratios or incorporating managed futures of particular maturities and hedge funds. The findings indicate that a portfolio comprising both conventional and alternative investments yields superior performance compared to a portfolio consisting solely of conventional investments. This project is primarily focused on employing a genetic algorithm to optimize portfolios that include REITs.

Our experimental study demonstrates that by decreasing total returns while increasing return amounts and thereby reducing risk, real estate investment enhances risk-adjusted returns. This primarily results from the lack of correlation between real estate and other asset types. Typically, portfolios that include real estate demonstrate a superior Sharpe ratio compared to those that do not incorporate such assets. Adding real estate-related assets to a portfolio makes the expected returns more concentrated around the mean and the negative skew stands out more than in portfolios that do not include real estate. This is likely associated with the decreased volatility and increased kurtosis, suggesting a greater probability of achieving returns that exceed the mean. While our findings indicate that real estate can enhance investment portfolio diversification, further research is necessary to thoroughly investigate the potential of employing genetic algorithms to optimize real estate portfolios. This study primarily derived the optimal weights from historical data. Utilizing prospective data, commonly referred to as price projections, is an effective way to enhance portfolio performance.

Limitations and future research directions. This work makes it easier for people to find the best mix of traditional and non-

traditional investment opportunities, which is a big step toward creating a complex multicriteria optimization model. This study offers a refined understanding of investment performance in real-world scenarios by analyzing how variables can sometimes diverge from typical patterns, which is in contrast to earlier research. This study addresses a gap in the existing literature by optimizing portfolios through the integration of traditional and non-traditional investments, such as real estate investment trusts (REITs). It provides insights into the challenges of risk management and diversification within the global financial landscape.

This research is essential for both academics and financial sector experts due to its comprehensive examination and actionable suggestions. The inclusion of alternative assets significantly enhances portfolio efficiency, as evidenced by the Sharpe ratio in most of the combinations analyzed.

Making multiple investments is crucial to leveraging the benefits of diversification. Investors with substantial bond and stock portfolios can manage interest rate risk by recalibrating their equity and bond ratios, which may include hedge funds, and by monitoring futures with designated maturities. The findings indicate that a portfolio incorporating unconventional assets outperformed one composed exclusively of traditional investments. The main aim of this initiative was to enhance real estate investment trust (REIT) portfolios through the application of a genetic algorithm. By minimizing overall returns and increasing return amounts thereby mitigating risk our experimental analysis indicates that real estate investment elevates risk-adjusted returns. The primary explanation for this phenomenon lies in the lack of correlation between various asset types and real estate. Real estate-heavy portfolios may exhibit a higher Sharpe ratio in comparison to those lacking such assets.

Merging real estate-related assets results in a greater degree of negative skewness and a more concentrated return around the mean compared to not combining them. This situation likely stems from the reduction in volatility and the rise in kurtosis, which indicate a higher probability of returns exceeding the mean.

Even though our results show that real estate could help make investment portfolios more diverse, more research needs to be done to fully assess how useful it would be to use genetic algorithms to optimize real estate portfolios. This study primarily utilized historical data to determine the optimal weights. By utilizing prospective data, commonly referred to as price projections, it is possible to improve portfolio performance to a certain degree. In future researchers can include the impact taxes while calculating the overall returns of the portfolio and can also apply other portfolio performance measures as well.

Data availability

Provided in Supplementary file.

Received: 14 August 2024; Accepted: 7 March 2025;

Published online: 03 April 2025

References

- Adiguzel Mercangoz B (2019) Particle swarm algorithm: an application on portfolio optimization. In: Jhuma R, Anirban M, Sedhan KD, Goran K (eds) Metaheuristic approaches to portfolio optimization. IGI Global
- Aithal PK, Geetha M, Dinesh U, Savitha B, Menon P (2023) Real-time portfolio management system utilizing machine learning techniques. *IEEE Access* 11:32595–32608
- Anderson RI, Benefield JD, Hurst ME (2015) Property-type diversification and REIT performance: an analysis of operating performance and abnormal returns. *J Econ Finance* 39. <https://doi.org/10.1007/s12197-012-9232-0>
- Block RL (2012) Investing in REITs: real estate investment trusts. Wiley
- Bonato M, Cepni O, Gupta R, Pierdzioch C (2022) Forecasting realized volatility of international REITs: The role of realized skewness and realized kurtosis. *J Forecast* 41(2):303–315
- Cheng P, Roulac SE (2007) REIT characteristics and predictability. *Int Real Estate Rev* 10. <https://doi.org/10.53383/100082>
- Cho JH, Elshahat AF (2011) Predicting time-varying long-run variance-modified component GARCH model approach. *J Financ Econ Pract* 11(1):52–68
- Chou YH, Kuo, SY, Lo YT (2017) Portfolio optimization based on funds standardization and genetic algorithm. *IEEE Access* 5. <https://doi.org/10.1109/access.2017.2756842>
- Chui AC, Titman S, Wei KJ (2003). The cross section of expected REIT returns. *Real Estate Econ* 31. <https://doi.org/10.1111/1540-6229.00073>
- Cici G, Gorgel J, Gibson S (2011) Can fund managers select outperforming REITs? Examining fund holdings and trades. *Real Estate Econ* 39. <https://doi.org/10.1111/j.1540-6229.2010.00304.x>
- Conlon T, Crotter J, Kynigakis I (2021) Machine learning and factor-based portfolio optimization. Michael J. Brennan Irish Finance Working Paper Series Research Paper No. 21. <https://doi.org/10.2139/ssrn.3889459>
- Dallagnol V, van den Berg J, Mous L (2009) Portfolio management using value at risk: a comparison between genetic algorithms and particle swarm optimization. *Int J Intell Syst* 24(7):766–792
- Daniušis P, Vaitkus Pr (2009) Supervised Feature Extraction Using Hilbert-Schmidt Norms. In: Corchado E, Yin H (eds) *Intelligent Data Engineering and Automated Learning - IDEAL 2009*, 25–33, Berlin, Heidelberg, Springer Berlin Heidelberg
- Deliktaş D, Ustun O (2023) Multi-objective genetic algorithm based on the fuzzy MULTIMOORA method for solving the cardinality constrained portfolio optimization. *Appl Intell* 53(12):14717–14743
- DeMiguel V, Nogales F (2009) Portfolio selection with robust estimation. *Oper Res* 57(3):560–577
- Deng G, Dulaney T, McCann C, Wang O (2013) Robust portfolio optimization with Value-at-Risk-adjusted Sharpe ratios. *J Asset Manag* 14(5):293–305
- Deng W, Polak P, Safikhani A, Shah R (2024) A Unified Framework for Fast Large-Scale Portfolio Optimization. *Data Sci Sci* 3(1):2295539
- Desmettre S, Korn R, Ruckdeschel P, Seifried F (2015) Robust worst-case optimal investment. *OR Spectr* 37:677–701
- Ding KW, Chen ZY, Huang NJ (2018) Robust mean variance optimization problem under Rényi divergence information. *Optimization* 67(2):287–307
- Doan X, Li X, Natarajan K (2015) Robustness to dependency in portfolio optimization using overlapping marginals. *Oper Res* 63:1468–1488
- Dupacova J, Kopa M (2014) Robustness of optimal portfolios under risk and stochastic dominance constraints. *Eur J Oper Res* 200:55–74
- Elbannan MA (2015) The capital asset pricing model: an overview of the theory. *Int J Econ Financ* 7(1):216
- Faridi S, Madanchi Zai M, Daneshvar A, Shahverdian S, Rahnamay Roodposhti F (2023) Portfolio rebalancing based on a combined method of ensemble machine learning and genetic algorithm. *J Financ Rep Account* 21(1):105–125
- Feng K, Li Q (2014) Using stepwise regression and support vector regression to comprise REITs' portfolio, 2014 IEEE 7th Joint International Information Technology and Artificial Intelligence Conference, Chongqing, China, pp 158–162. <https://doi.org/10.1109/ITAIC.2014.7065026>
- Gunjan A, Bhattacharyya S (2023) A brief review of portfolio optimization techniques. *Artif Intell Rev* 56(5):3847–3886
- Hansz JA, Zhang Y, Zhou T (2017) An Investigation into the substitutability of equity and mortgage REITs in real estate portfolios. *J Real Estate Financ Econ* 54. <https://doi.org/10.1007/s11146-016-9572-1>
- Hastings HM, Waner S (1985) Principles of evolutionary learning design for a stochastic neural network Biosystems 18(1):105–109. [https://doi.org/10.1016/0303-2647\(85\)90063-2](https://doi.org/10.1016/0303-2647(85)90063-2)
- Hausler J, Ruschinsky J, Lang M (2018) News-based sentiment analysis in real estate: a machine learning approach. *J Prop Res* 35(4):344–371
- Hedges LV, Olkin I (1985) *Statistical methods for meta-analysis*. Academic press, Orlando
- Hu Y, Sun X, Nie X, Li Y, Liu L (2019) An enhanced LSTM for trend following of time series. *IEEE Access* 7:34020–34040
- Huang C-F (2012) A hybrid stock selection model using genetic algorithms and support vector regression. *Appl Soft Comput* 12(2):807–818
- Katoch S, Chauhan S, Kumar V (2021) A review on genetic algorithm: past, present, and future. *Multimed Tools Appl* 80(5):8091–8126. <https://doi.org/10.1007/s11404-020-10139-6>
- Kaucic M (2019) Equity portfolio management with cardinality constraints and risk parity control using multi-objective particle swarm optimization. *Comput Oper Res* 109:300–316
- Kumar S, Sharma S (2021) A genetic algorithm for feature selection and parameter optimization in machine learning. *J Expert Syst Appl* 187. <https://doi.org/10.1016/j.eswa.2021.115990>

- Lee S, Stevenson S (2005) The case for REITs in the mixed-asset portfolio in the short and long run. *J Real Estate Portf Manag* 11(1):55–80. <https://doi.org/10.1080/10835547.2005.12089711>. 2005/01/01
- Lee S, Stevenson S (2004) The case for REITs in the mixed-asset portfolio in the short and long run. Henley Business School, Reading University, Real Estate & Planning Working Papers, 11
- Lee YH, Pai TY (2010) REIT volatility prediction for skew-GED distribution of the GARCH model. *Expert Syst Appl* 37. <https://doi.org/10.1016/j.eswa.2009.11.044>
- Lertwachara K (2007) Selecting stocks using a genetic algorithm: a case of real estate investment trusts (REITs). *Kasetsart J Soc Sci* 28(28):106–116
- Li N, Li RYM, Pu R (2021) What is in a name? A modern interpretation from housing price in Hong Kong. *Pac Rim Prop Res J* 27(1):55–74. <https://doi.org/10.1080/14445921.2021.1961182>. 2021/01/02
- Li RYM, Song L, Li B, Crabbe MJC, Yue X-G (2022) Predicting carpark prices indices in Hong Kong Using AutoML. *Comput Model Eng Sci* 134(3):2247–2282. <https://doi.org/10.32604/cmescs.2022.020930>
- Li J, Lei L (2011) Determinants and information of REIT pricing. *Appl Econ Lett* 18. <https://doi.org/10.1080/13504851.2010.543074>
- Li S, Wang H (2018) Traditional literature review and research synthesis. In A. Phakiti, P. De Costa, L. Plonsky, & S. Starfeld (Eds.) *The Palgrave Handbook of applied linguistics research methodology* (pp. 123–144). Palgrave-MacMillan
- Li W, Huyen J, Xiao L, Tighe S, Pei L (2019) International roughness index prediction based on multigranularity fuzzy time series and particle swarm optimization. *Expert Syst Appl* X 2:100006
- Ling DC, Naranjo A (2015) Returns and information transmission dynamics in public and private real estate markets. *Real Estate Econ* 43. <https://doi.org/10.1111/1540-6229.12069>
- Ling DC, Naranjo A, Ryngaert MD (2000) The predictability of equity REIT returns: time variation and economic significance. *J Real Estate Finance Econ* 20. <https://doi.org/10.1023/A:1007821103728>
- Liu L, Chen Q (2020) How to compare market efficiency? The Sharpe ratio based on the ARMA-GARCH forecast. *Financ Innov* 6. <https://doi.org/10.1186/s40854-020-00200-6>
- Lo AW (2002) The statistics of Sharpe ratios. *Financ. Anal J* 58. <https://doi.org/10.2469/faj.v58.n4.2453>
- Loo WK (2019) Predictability of HK-REITs returns using artificial neural network. *J Prop Invest Finance* 38. <https://doi.org/10.1108/JPIF-07-2019-0090>
- Loo WK (2020) Performing technical analysis to predict Japan REITs' movement through ensemble learning. *J Prop Invest Finance* 38. <https://doi.org/10.1108/JPIF-01-2020-0007>
- Markowitz H (1952) Portfolio selection*. *J Finance* 7(1):71–99
- Michaud RO (1989) The Markowitz optimization enigma: is 'optimized' optimal. *Financ Anal J* 45. <https://doi.org/10.2469/faj.v45.n1.31>
- Michaud RO (1998) *Efficient asset management: a practical guide to stock portfolio optimization and asset allocation*. Oxford University Press
- Mueller GR, Mueller AG (2019) Real estate return cycles and the contributions to a mixed asset portfolio. *African Real Estate Society (AfRES)*, p. 112
- Nafia A, Yousfi A, Echaoui A (2023) Equity-market-neutral strategy portfolio construction using LSTM-based stock prediction and selection: an application to S&P500 consumer staples stocks. *Int J Financ Stud* 11(2):57
- Olanrele O, Said R, Bin Daud M (2014) Divided based return forecast as benchmark for REIT performance. *OIDA Int J Sustain Dev* 7
- Pandolfo G, Iorio C, Siciliano R, D'Ambrosio A (2019) Robust mean-variance portfolio through the weighted Lp depth function. *Ann Oper Res*. <https://doi.org/10.1007/s10479-019-03474-x>
- Quaranta AG, Zaffaroni A (2008) Robust optimization of conditional value at risk and portfolio selection. *J Bank Financ* 32(10):2046–2056
- Rather AM (2021) LSTM-based deep learning model for stock prediction and predictive optimization model. *EURO J Decis Process* 9:100001. <https://doi.org/10.1016/j.ejdp.2021.100001>. 2021/01/01/
- Scutella MG, Recchia R (2013) Robust portfolio asset allocation and risk measures. *Ann Oper Res* 204(1):145–169
- Sharpe WF (1998) The Sharpe ratio. *Streetwise-Best J Portfolio Manag* 3. <https://doi.org/10.1515/9781400829408-022>
- Shen J (2021) Distress risk and stock returns on equity REITs. *J Real Estate Financ Econ* 62. <https://doi.org/10.1007/s11146-020-09756-7>
- Shen J, Hui EC, Fan K (2021) The beta anomaly in the REIT market. *J Real Estate Financ Econ* 63. <https://doi.org/10.1007/s11146-020-09784-3>
- Sirmans S, Friday S, Price R (2006) Do management changes matter? An empirical investigation of REIT performance. *J Real Estate Res* 28. <https://doi.org/10.1080/10835547.2006.12091173>
- Sivanandam SN, Deepa SN (2007) *Introduction to genetic algorithms*. Springer
- Surtee TGH, Alagidede IP (2023) A novel approach to using modern portfolio theory. *Borsa Istanbul Rev* 23(3):527–540. <https://doi.org/10.1016/j.bir.2022.12.005>
- Swinkels L (2023) Empirical evidence on the ownership and liquidity of real estate tokens. *Financ Innov* 9. <https://doi.org/10.1186/s40854-022-00427-5>
- Vassiadou-Zeniou C, Zenios SA (1996) Robust optimization models for managing callable bond portfolios. *Eur J Oper Res* 91(2):264–273
- Wang X, Xiao X, Xiao Z (2016) S-REITs' performance forecast using a small sample model associating support vector machine with vector auto-regression model. *Int J Innov Comput Inf Control* 12:15–40
- Wang Z, Zhang X, Zhang Z, Sheng D (2022) Credit portfolio optimization: a multi-objective genetic algorithm approach. *Borsa Istanbul Rev* 22(1):69–76
- Xidonas P, Hassapis C, Soulis J, Samitas A (2017) Robust minimum variance portfolio optimization modelling under scenario uncertainty. *Econ Model* 64:60–71
- Yaman I, Dalkılıç TE (2021) A hybrid approach to cardinality constraint portfolio selection problem based on nonlinear neural network and genetic algorithm. *Expert Syst Appl* 169:114517
- Yang J, Zhou Y, Leung W (2012) Asymmetric correlation and volatility dynamics among stock, bond, and securitized real estate markets. *J Real Estate Financ Econ* 45(2):491–521. <https://doi.org/10.1007/s11146-010-9265-0>
- Yang MD, Yang YF, Su TC, Huang KS (2014) An efficient fitness function in genetic algorithm classifier for land use recognition on satellite images. *Sci World J* 14. <https://doi.org/10.1155/2014/264512>
- Yeo LLX, Cao Q, Quek C (2023) Dynamic portfolio rebalancing with lag-optimised trading indicators using SeroFAM and genetic algorithms. *Expert Syst Appl* 216:119440
- Yu L, Wang S, Wen F, Lai KK (2012) Genetic algorithm-based multi-criteria project portfolio selection. *Ann Oper Res* 197:71–86

Author contributions

Substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work: conceptualization: Li Xu; methodology: Liviu Marian Matic, Codruta-Daniela Pavel; software: Juan Felipe Espinosa Cristia; data acquisition: Juan Felipe Espinosa Cristia; formal analysis: Li Xu; data curation: Rui Dias; validation: Rui Dias. Drafting the work or revising it critically for important intellectual content: writing—original draft preparation: Li Xu; writing—review and editing: Liviu Marian Matic.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1057/s41599-025-04715-0>.

Correspondence and requests for materials should be addressed to Li XU.

Reprints and permission information is available at <http://www.nature.com/reprints>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2025