Strategic Change in Resolving the Efficiency-Equity Dilemma:
A Novel Approach to Portfolio Selection

Rania A. Azmi
Independent Researcher
Kuwait
Email: rania.a.azmi@gmail.com

Charbel Salloum
Métis Lab,
EM Normandie Business School,
Le Havre, France
Email: csalloum@em-normandie.fr

Renato Pereira
Business Research Unit, ISCTE Instituto Universitário de Lisboa,
Portugal
Email: renato.pereira@iscte-iul.pt

Hajer Jarrar
CERIIM – Research Center in Managerial Intelligence and Innovation,
La Rochelle Business School,
La Rochelle, France
Email: jarrarh@excelia-group.com

Jean-Francois Verdie
Department of Economy and Finance
TBS Business School
Toulouse
France
Email: jf.verdie@tbs-education.fr

Acknowledgements
The authors extend their gratitude to Professor Mehrdad Tamiz for his invaluable guidance in this research. Despite his passing, Professor Tamiz's enduring example and dedication to operational research methodologies in finance continue to inspire. Additionally, the authors acknowledge the financial support from Fundação para a Ciência e a Tecnologia, grant UIDB/00315/2020 (DOI: 10.54499/UIDB/00315/2020).

Strategic Change in Resolving the Efficiency-Equity Dilemma:
A Novel Approach to Portfolio Selection

Abstract

This paper introduces an innovative portfolio selection methodology that incorporates Extended Goal Programming (EGP) to address the efficiency-equity tradeoff in international portfolio management. Unlike traditional methods, EGP integrates multiple-objective optimization, allowing for a balanced consideration of risk, return, and correlation simultaneously. This study not only advances the theoretical framework of portfolio management by extending the principles of Modern Portfolio Theory (MPT) but also provides empirical evidence of EGP's robustness across various market conditions, including financial crises. Utilizing data from five major global stock markets, which collectively represent over 70% of global market value, the results demonstrate that EGP-constructed portfolios outperform both global and market-specific benchmarks. The research contributes to the literature by offering a flexible, adaptable tool for decision-makers, enabling them to tailor portfolio strategies to diverse investor goals and volatile market environments. This study's findings have significant implications for both academics and practitioners, paving the way for more resilient and optimized portfolio management practices.

Keywords: Portfolio Selection, Efficiency-Equity Tradeoff, Extended Goal Programming, International Stock Markets.

Introduction

The rapid evolution of global stock markets, exacerbated by recent crises such as the financial downturn of 2007/2008 and the COVID-19 pandemic, has heightened the need for more sophisticated and robust portfolio management strategies. Traditional portfolio selection methodologies, notably Markowitz's Modern Portfolio Theory (MPT), have long focused on optimizing single objectives, such as risk or return. While MPT has been foundational in guiding investment decisions, its limitations have become increasingly evident, particularly in volatile markets where correlations among asset classes tend to increase, thereby diminishing the benefits of diversification (Markowitz, 1995; Sharpe, 1985).

In response to these challenges, this study introduces a novel portfolio selection methodology that employs Extended Goal Programming (EGP) to simultaneously address multiple objectives—risk, return, and correlation—within the context of international stock markets. By integrating EGP into portfolio management, this research offers a more holistic decision-making framework that extends beyond the traditional single-objective focus of MPT. EGP's unique ability to balance the trade-off between efficiency (optimization) and equity (balance) provides decision-makers with a versatile tool for navigating the complexities of modern financial markets.

This study's contributions are threefold. First, it advances the theoretical framework of portfolio management by incorporating EGP, which allows for a nuanced optimization of multiple objectives. Second, it empirically validates the effectiveness of EGP across various market conditions, demonstrating its superiority in constructing portfolios that perform well even during financial crises. Third, it positions EGP as a practical and adaptable tool for portfolio managers, enabling them to tailor investment strategies to diverse investor goals and market scenarios.

The results of this study suggest that portfolios constructed using EGP models achieve superior performance against both global benchmarks and market-specific indices. This research not only contributes to the existing literature by filling a gap in multi-objective portfolio optimization but also provides actionable insights for practitioners seeking to enhance their portfolio management strategies in an increasingly uncertain global market environment.

Literature Review

Historical Approaches to Portfolio Selection

The foundation of modern portfolio selection is rooted in the work of Markowitz (1952), who introduced Modern Portfolio Theory (MPT). MPT emphasizes diversification by optimizing the trade-off between risk and return, primarily through single-objective optimization models. Over the decades, Markowitz's framework has been widely adopted due to its practical applicability, particularly in the context of normal market conditions. However, the efficacy of MPT has been questioned during periods of financial crises, where correlations among asset classes tend to increase, diminishing the benefits of diversification (Markowitz, 1995; Sharpe, 1985). Despite its limitations, MPT remains a cornerstone in the field of portfolio management, underscoring the importance of risk-return optimization.

Goal Programming in Portfolio Selection

As the limitations of single-objective optimization became apparent, Goal Programming (GP) emerged as a versatile alternative for portfolio selection. GP allows decision-makers to simultaneously consider multiple objectives, accommodating diverse investor preferences and constraints (Azmi & Tamiz, 2010; Aouni et al., 2014). The flexibility of GP lies in its ability to balance competing objectives, such as risk, return, and other financial goals, through the selection of appropriate achievement functions. The adaptability of GP has made it a popular tool in addressing the complexities of modern financial markets, particularly during volatile periods (Tamiz & Jones, 1997).

Extended Goal Programming (EGP) in Portfolio Management

Building on the principles of GP, Extended Goal Programming (EGP) introduces further sophistication by integrating multiple objectives and strategic trade-offs. EGP models are particularly useful in scenarios where decision-makers must balance efficiency (optimization) and equity (balance) within portfolio selection (Jones & Tamiz, 2010). The introduction of the parameter αα in EGP models allows for fine-tuning between these competing objectives, offering a nuanced approach to portfolio management that is responsive to varying market conditions.

Unlike traditional Goal Programming (GP), which often requires a strict prioritization of objectives (Charnes, Cooper, & Ferguson, 1955), EGP allows for a more flexible, non-lexicographic evaluation of multiple objectives. This means that all goals can be considered simultaneously, rather than sequentially, which is particularly advantageous in complex financial environments where trade-offs between objectives are not always clear-cut (Romero, 2004). By adjusting the ααparameter, decision-makers can navigate the spectrum between pure optimization and balanced solutions, making EGP adaptable to different investor needs and market scenarios (Jones & Tamiz, 2010).

Besides, the normalization process in EGP ensures that different objectives—such as return, risk, and correlation—are comparable, even when measured in different units. This is crucial for portfolio management, where diverse metrics must be integrated into a cohesive decision-making framework (Tamiz & Jones, 1997). The flexibility and adaptability of EGP have been empirically validated in various studies, which show that EGP models can outperform traditional benchmarks, particularly during financial crises (Jatuphatwarodom et al., 2018).

Overall, EGP represents a significant advancement in the field of portfolio management, offering a sophisticated tool that accommodates the complexities of modern financial markets. Its ability to provide a range of strategic options tailored to different market conditions and investor preferences makes it an invaluable asset for both academic research and practical application (Romero, 2001).

Methodology

Main Methodology and Data Utilized

Portfolio selection models are fundamental in determining strategic investment approaches and can be broadly classified into two categories: single-objective optimization and multiple-objective optimization. Single objective optimization focuses on optimizing one function of one decision variable—such as minimizing risk subject to a return threshold—adhering closely to the pioneering methodology introduced by Markowitz in 1952. This classical approach underscores the essence of achieving specific financial targets under defined constraints. Contrastingly, multiple-objective optimization allows for the incorporation of various factors simultaneously, enhancing the decision-making process by minimizing unwanted deviations across all considered factors (Romero, 2004; Tamiz and Jones, 1997). This methodology is particularly effective in addressing the complexities of modern portfolio management, where the simultaneous consideration of risk, return, and correlation is crucial.

This paper delves into several Goal Programming (GP) achievement functions, with a special focus on the Extended Goal Programming (EGP) achievement function. EGP facilitates a strategic trade-off between equity and efficiency, allowing decision-makers to navigate between these objectives fluidly. The trade-offs between efficiency and balance are meticulously managed through the parameter α, which ranges from total focus on optimization ($\alpha = 0$, representing a Weighted GP achievement function) to a complete emphasis on balance ($\alpha = 1$, indicative of a Chebyshev GP achievement function).

Our exploration prioritizes the investigation of these efficiency-balance trade-offs, employing a non-lexicographic form of EGP that fosters a comprehensive evaluation of competing objectives rather than a singular focus. This approach is pivotal in enriching the quality of decision-making within portfolio management, as it allows the integration of multiple criteria that reflect the real-world complexities investors face. Moreover, the EGP methodology's flexibility in setting and adjusting weights and achievement functions offers a tailored solution landscape to decision-makers. This capability is crucial in presenting a spectrum of viable solutions, rather than a single optimal outcome, thereby accommodating diverse investor goals and preferences. The insights derived from these models are instrumental in shaping effective and strategic investment decisions, providing a robust framework that aligns with both current needs and future aspirations of investors.

Data Utilization and Portfolio Construction Methodology

Various models and real data are used for constructing and testing portfolios. This research provides a reliable methodology to construct investment portfolios with various solutions that more realistically consider a decision maker’s goals and preferences. The constructed portfolios utilize various Extended Goal Programming models to determine their constituents from a selection of 15 blue-chip stocks representing the top five financial markets in the world, which collectively account for over 70% of the world’s stock market value (a list of the stocks and their countries is provided in appendix I). The resulting portfolios are compared against each other, against the world’s benchmark, and against the benchmarks of their respective markets, namely: the US S&P 500, the UK FTSE 100, Japan’s NIKKEI 225, France’s CAC 40, and Switzerland’s SMI. The experiments use a construction period of 290 days - January 2020 to February 2021 - with 4,350 observations, and a testing period of 290 days - March 2021 to April 2022 - with 4350 observations. Return, risk and correlation are the three main factors used as criteria to construct and select portfolios in various EGP models. Table I details the list of the factors utilized across each variable (stock), together with the overall mean, standard deviation, minimum value, and maximum value for each factor for all stocks (variables).

INSERT TABLE I

Extended Goal Programming Models Constructed and Tested

In this study, various Extended Goal Programming (EGP) models are employed, each testing portfolio efficiency with respect to key performance metrics such as overall risk and return. These models are applied throughout both the construction and testing phases of the portfolio development process. The specific formulations for these models, including both general and normalized Weighted Goal Programming (WGP) models, are detailed in Appendices II and III, respectively.

$$MinA = \alpha D + (1-\alpha)\left\{\sum_{i=1}^{I}\left(\frac{w_{n_i}n_i}{K_i} + \frac{w_{p_i}p_i}{K_i}\right)\right\}$$

Subject to

$$\frac{w_{n_i}n_i}{k_i} + \frac{w_{p_i}p_i}{k_i} - D \leq 0 i = 1,2, \dots, I$$

$$f_i(x) + n_i - p_i = b_i i = 1,2, \dots, I$$

$$x \in F$$

$$n_i, p_i \geq 0 i = 1,2, \dots, I$$

Where:

A is the achievement function

Parameter α provides a trade-off between minimization of the weighted sum of unwanted deviation variables and minimization of the maximum deviation from the target values.

D Maximum weighted deviation from amongst the set of unwanted deviations

$w_{n_i}$is the preferential weight associated with the minimization of n_i

n_i is the negative deviational variable of the i^{th} goal

w_{p_i} is the preferential weight associated with the minimization of p_i

p_i is the positive deviational variable of the i^{th} goal

K_i is the normalization constant associated with the i^{th} goal

b_i represents the target level for the i^{th} goal

$f_i(x)$ is the i^{th} objective function

x_i Proportion of funds invested in the i^{th} asset

F represents the feasible region of the original multiple-objective problem.

I is the number of goals

There are seven constructed and tested EGP models in which the above formulation is used. Only the Parameter of "α" changes to different variations, effectively providing a trade-off between minimization of the weighted sum of unwanted deviation variables and minimization of the maximum deviation from the target values, as illustrated in Table II:

INSERT TABLE II

Table II illustrates the trade-off parameter, α, used in the Extended Goal Programming (EGP) models, which varies between 0 and 1. In these experiments, an α value of 0.5 is considered to provide a balanced trade-off between optimization and equity, in line with the underlying philosophies of the EGP framework (Jatuphatwarodom et al., 2018).

For the experiments conducted in this study, the strategy for the objective functions is structured as follows: The objective for Return (RE) is to achieve a value greater than the target value (b_R), where higher values are preferable, and negative deviational variables are penalized to discourage underperformance. For Risk (RI), the goal is to keep risk below the target value (b_RI), with lower values being preferable and positive deviational variables penalized to discourage excess risk. Similarly, for Correlation (CO), the aim is to maintain correlation levels below the target value (b_CO), with lower values being preferable and positive deviational variables penalized to limit high correlation.

It is important to note that all target values in this research are strictly positive and measured in various units. Therefore, percentage normalization is applied, where the normalized factor (k_i) for each objective's unwanted deviational variable corresponds to its target value, as documented by Jones and Tamiz (2010).

Results

Constructed Portfolios and Performance Evaluation

The seven main Extended Goal Programming (EGP) models utilized in this research resulted in intriguing portfolio constituents, establishing a clear tradeoff between efficiency and balance. It is important to note that in this context, "efficiency" refers to "optimization," which methodologically corresponds to the use of Weighted Goal Programming (WGP). Conversely, "balance" refers to "equity," which methodologically denotes the use of Chebyshev Goal Programming (CGP). The EGP achievement function provides a versatile means to derive a range of solutions from a single set of data and weights. Specifically, using $\alpha = 0$ in the model signifies an emphasis on minimizing the weighted sum of unwanted deviations, whereas using $\alpha = 1$ spreads the deviations, aiming to keep the largest unwanted deviation as minimal as possible. Table III displays the key parameters from these experiments.

INSERT TABLE III

When evaluating the performance of the constructed portfolios, it is crucial to consider the overall risk and return, as well as the number of constituent stocks. These factors are essential for a comprehensive comparison. Table IV presents these results, detailing the return, risk, number of stocks, their proportions, and the names of stocks for the key models tested across the seven constructed portfolios:

INSERT TABLE IV

Table IV provides the overall return, risk, and details such as the number of stocks, stock names, and their proportions for all models tested in this study. Comparisons between the constructed portfolios reveal that the EGP1 and EGP2 models generate the best returns and exhibit the lowest risk levels among the seven portfolios. Conversely, the EGP7 model shows the least favorable outcomes in terms of both return and risk. These results are particularly notable as they reflect the diverse alternatives available to decision-makers, each model representing a different balance between efficiency and equity. Specifically, the EGP1 model, with an $\alpha = 0$, optimizes for efficiency, while the EGP7 model, with an $\alpha = 1$, focuses on balance or equity.

This distinction suggests that the trade-off leaning towards efficiency (EGP1) tends to outperform the balance-oriented approach (EGP7) under the conditions tested. Therefore, decision-makers might prefer the efficiency-oriented models when selecting portfolio constituents to achieve superior risk-return outcomes. Further evaluation involves comparing the performance of these portfolios against relevant benchmarks that align with the composition of most stocks, as well as market-specific benchmarks. Tables V and VI in the subsequent section provide detailed comparisons of risk and return across the seven portfolios, facilitating a deeper understanding of each model's performance relative to broader market indices.

Evaluation of the Constructed Portfolios

INSERT TABLE V

Table V provides an evaluation of the investment performance of the portfolios constructed in this study, focusing specifically on the overall risk relative to the MSCI World index, which comprises 1,559 stocks, and other market indices that align with the constituents of each portfolio. For instance, if a portfolio includes stocks from the U.S. market, it is benchmarked against both the U.S. market index (S&P 500 with 500 constituents) and the global MSCI World index. Similarly, portfolios containing stocks from the UK, Japan, France, and Switzerland are compared against their respective local market indices—FTSE 100, NIKKEI 225, CAC 40, and SMI.

For example, a -0.03% percent change for the EGP1 model against the MSCI World index indicates that the risk of the EGP1 portfolio is 0.03% lower than that of the MSCI World benchmark during the testing period. Additionally, this portfolio's risk performance is compared with the benchmarks of the UK, Japan, France, and Switzerland, reflecting the international diversity of its constituents as outlined in Table IV. Across these comparisons, the EGP1 portfolio consistently demonstrates a lower risk profile relative to both the global benchmark and the specific market indices, which is noteworthy given the smaller scale of its constituents compared to those of the benchmarks.

The EGP7 portfolio, on the other hand, exhibits a higher risk than the benchmarks, highlighting variations in performance across the different EGP models. Table VI will further elaborate on these performance comparisons by focusing on return metrics, providing a comprehensive view of how each portfolio stands in terms of both risk and return against the designated benchmarks.

INSERT TABLE VI

Table IV provides a detailed comparison of the returns between the constructed portfolios and their corresponding benchmarks. For instance, the EGP1 portfolio exhibits a return that surpasses the global MSCI World benchmark by 0.073%. Further analysis reveals that the EGP1 portfolio also outperforms four other specific market benchmarks—this includes benchmarks for the US, UK, Japan, and France, as detailed previously in Table IV. This portfolio consistently achieves higher returns than all related market indices.

This pattern is observed across all seven portfolios tested, where each portfolio's return exceeds that of any benchmark used in this study, as further illustrated in Table VI. Notably, among the fifteen high-capitalization stocks selected for inclusion in these portfolios, only four to five stocks consistently delivered superior performance compared to their respective market indices and the global benchmark. This outcome highlights the effectiveness of the portfolio selection strategy implemented, which leverages a refined approach to stock selection that aligns with achieving higher returns than those offered by conventional market indices.

Results Key Findings

The study tested seven Extended Goal Programming (EGP) models, each varying by the parameter αα, which represents the trade-off between efficiency (optimization) and equity (balance). The models range from EGP1 (α=0.0α=0.0, focusing entirely on optimization) to EGP7 (α=1.0α=1.0, focusing entirely on balance).

Performance of EGP1 and EGP2 Models:

- EGP1 and EGP2, with lower αα values (0.0 and 0.2 respectively), consistently demonstrated superior performance in terms of return and risk. These models optimized for efficiency, leading to portfolios that outperformed the global MSCI World benchmark and market-specific indices such as the S&P 500, FTSE 100, and NIKKEI 225.
- Significant Observation: The EGP1 model, in particular, showed the best performance, with a portfolio return exceeding the MSCI World benchmark by 0.073% and a risk profile 0.03% lower than the benchmark. This result highlights the effectiveness of efficiency-focused models in delivering high returns with relatively low risk.

Comparison with Higher αα Models (EGP6 and EGP7):

- EGP6 and EGP7, with higher αα values (0.8 and 1.0 respectively), aimed at balancing optimization with equity. However, these models exhibited higher risk and lower returns compared to their lower ααcounterparts.
- Significant Observation: The EGP7 model, which fully prioritizes balance, showed the least favorable outcomes, with a return only 0.045% higher than the MSCI World benchmark but with significantly higher risk (1.365%).

Balanced Approach in EGP4 and EGP5:

- EGP4 and EGP5 models, with moderate αα values (0.5 and 0.6 respectively), struck a balance between optimization and equity. These models showed moderate performance, with returns and risks falling between the efficiency-focused and balance-focused models.
- Significant Observation: EGP4, with an αα of 0.5, demonstrated a well-rounded performance, achieving a balanced trade-off between return and risk, making it suitable for decision-makers who prioritize a more balanced approach.

The results suggest that models focusing on efficiency (lower αα values) tend to outperform those focusing on balance, particularly in terms of achieving higher returns with lower risk.

The EGP1 model emerged as the most effective in this regard, making it a strong candidate for decision-makers seeking to optimize their portfolios for performance.

Conversely, the models with higher αα values, while still outperforming benchmarks, exhibited higher risk levels, which may be less desirable in volatile market conditions. Decision-makers should consider the trade-offs between efficiency and balance when selecting the appropriate model for portfolio construction.

Discussion

Theoretical Contributions

This study makes several key theoretical contributions to the field of portfolio management and financial decision-making.

This research extends the traditional framework of Modern Portfolio Theory (MPT) by incorporating Extended Goal Programming (EGP) into the portfolio selection process. MPT, originally introduced by Markowitz (1952), has been foundational in optimizing risk-return trade-offs through single-objective optimization. However, MPT's limitations, particularly during periods of market instability when correlations between assets increase (Markowitz, 1995; Sharpe, 1985), necessitate more robust methodologies. By employing EGP, this study introduces a multi-objective optimization approach that balances risk, return, and correlation simultaneously, thereby addressing the shortcomings of single-objective models (Romero, 2004; Tamiz & Jones, 1997).

The introduction of the αα parameter in EGP models allows for a flexible trade-off between efficiency (optimization) and equity (balance). This is a significant theoretical contribution as it enhances the adaptability of goal programming within financial decision-making frameworks. The parameter αα can be adjusted to reflect varying strategic priorities, offering decision-makers the ability to tailor portfolio strategies according to specific market conditions and investor objectives (Jones & Tamiz, 2010). This adaptability is particularly valuable in scenarios where market volatility requires dynamic portfolio adjustments (Azmi & Tamiz, 2010).

Through empirical testing using data from major global stock markets, this study validates the theoretical benefits of EGP models. The results demonstrate that portfolios constructed using EGP models, particularly those with lower αα values (e.g., EGP1 and EGP2), achieve superior performance compared to global and market-specific benchmarks. This empirical validation reinforces the applicability of multi-objective optimization techniques in real-world portfolio management, aligning with the findings of previous studies on the utility of goal programming in financial contexts (Aouni et al., 2014; Bravo et al., 2010).

Practical Implications

The findings of this study also have significant practical implications for portfolio managers, investors, and financial institutions.

The superior performance of the EGP1 and EGP2 models, which focus on efficiency with lower αα values, suggests that portfolio managers can achieve better returns with lower risk by prioritizing optimization strategies. In practice, this means that decision-makers should consider adopting efficiency-oriented models when constructing portfolios, particularly in volatile markets. This approach aligns with the strategic objectives of minimizing risk while maximizing returns, as emphasized in contemporary portfolio management practices (Tamiz & Azmi, 2019).

The flexibility Inherent In EGP models allows portfolio managers to dynamically adjust their strategies based on prevailing market conditions. For instance, during periods of high volatility, an efficiency-focused model like EGP1 might be more appropriate to mitigate risks and capitalize on return opportunities. Conversely, in more stable conditions, a model with a balanced approach, such as EGP4, could be utilized to achieve a broader range of objectives (Jatuphatwarodom et al., 2018). This adaptability makes EGP a valuable tool for managing portfolios across varying market environments.

EGP models provide a customizable framework that can be tailored to fit the specific risk-return profiles of different investors. This capability is particularly useful for financial advisors and portfolio managers who need to design investment strategies that align with the unique preferences and goals of their clients. For example, clients with a higher risk tolerance might prefer portfolios based on models with lower αα values, while more risk-averse clients might benefit from strategies that incorporate a more balanced approach (Dash & Kajiji, 2014).

The ability of EGP models to outperform benchmarks with fewer portfolio constituents suggests that more concentrated portfolios, optimized using advanced techniques, can be both effective and manageable. This has practical implications for investors seeking to maximize returns while minimizing risk through strategic asset selection. Concentrated portfolios, when constructed using EGP, can offer a more focused approach to risk management, providing a pragmatic solution for decision-makers aiming to optimize trade-offs between efficiency and equity (Gerdessen & DeVries, 2015).

The findings of this study can be directly applied to the development of automated Investment platforms and advisory services. EGP models can be integrated into these platforms to provide a sophisticated tool for optimizing portfolios in real-time. As financial markets continue to grow in complexity, the ability to dynamically adjust investment strategies using models like EGP will become increasingly valuable. This makes EGP an essential component of modern portfolio management, particularly in automated and algorithm-driven investment contexts (Messaoudi et al., 2015).

Broader Implications

The broader implications of this research extend to the evolving landscape of financial decision-making. The successful application of EGP in portfolio selection challenges the traditional reliance on single-objective optimization models, advocating for a more holistic approach that considers multiple competing objectives. This shift could influence how financial institutions and individual investors approach portfolio construction, potentially leading to more adaptive and resilient investment strategies (Romero, 2001; Ayyagari et al., 2021).

Moreover, the flexibility and robustness of EGP models suggest that they could be integrated into broader financial decision-making processes, including stress testing and scenario analysis. As financial markets continue to experience rapid changes, the ability to incorporate multiple objectives and dynamically adjust strategies will be crucial for maintaining competitiveness and achieving long-term financial goals (Alexander & Baptista, 2009).

Conclusion

In times of turmoil, it is crucial to equip decision-makers with reliable frameworks that enhance their decision-making capabilities. This research has introduced and tested a robust methodological and scientific framework for constructing and selecting investment portfolios that align with decision-makers' preferences, focusing on the fundamental factors of risk, return, and correlation. By utilizing various Extended Goal Programming (EGP) models, this study has explored multiple strategic alternatives, enhancing our understanding of portfolio performance across different market scenarios. A significant advantage of the EGP approach lies in its ability to offer not just a single solution but a spectrum of options that cater to varying strategic needs. This adaptability allows decision-makers to choose the most appropriate solution that aligns with their specific objectives and preferences. The diversity of solutions provided by the seven EGP models used in this study underscores the framework’s capability to illustrate a clear trade-off between efficiency and balance, offering decision-makers a granular control over their investment strategies. Besides, this study employs international benchmarks to assess the performance of these portfolios, providing valuable insights that benefit both practitioners and academics. The findings suggest that using publicly available financial data, decision-makers can effectively apply the proposed EGP methodology to construct portfolios that optimize the overall risk and return parameters. The target values of the main construction factors—risk, return, and correlation—not only define the utility of the portfolios but also reflect the strategic priorities of the decision-makers. The nuanced trade-offs between efficiency and balance highlighted by this research prove particularly beneficial in scenarios where decision-makers prioritize lowering risk while maximizing returns. However, the flexibility of the EGP models also supports scenarios where a balanced approach is preferred, accommodating needs across different regions, asset classes, and sectors. This versatility makes EGP an invaluable tool in the dynamic field of portfolio management, offering avenues for further research into its applications across broader financial contexts. This study paves the way for future investigations into the integration of EGP models with emerging technologies and more complex market scenarios, potentially expanding the scope of strategic financial decision-making tools available to investors and managers worldwide.

References

Abdulaziz, F., & Masmoudi, M. (2013). A multiple objective stochastic portfolio selection problem with random Beta. *International Transactions in Operational Research, 21*, 919–933. https://doi.org/10.1111/itor.12037

Alexander, G., & Baptista, A. (2009). Stress testing by financial intermediaries: Implications for portfolio selection and asset pricing. *Journal of Financial Intermediation, 18*, 65–92. https://doi.org/10.1016/j.jfi.2008.02.004

Anser, M. K., Khan, M. A., Zaman, K., Nassani, A. A., Askar, S. E., Abro, M. M. Q. A., & Kabbani, A. (2021). Financial development during COVID-19 pandemic: The role of coronavirus testing and functional labs. *Financial Innovation*, *7*(9). https://doi.org/10.1186/s40854-021-00226-4

Aouni, B., Colapinto, C., & La Torre, D. (2014). Portfolio management through the goal programming model: Current state-of-the-art. *European Journal of Operational Research, 234*, 536–545. https://doi.org/10.1016/j.ejor.2013.09.040

Ayyagari, M., Demirguc-Kunt., A., & Maksimovic, V. (2021). How common are credit-less recoveries? Firm-level evidence on the role of financial markets in crisis recovery. *Journal of Corporate Finance, 69*. https://doi.org/10.1016/j.jcorpfin.2021.102016.

Azmi, R. A, & Tamiz, M. (2010). A review of goal programming for portfolio selection. In D. F. Jones, M. Tamiz & J. Ries (Eds.), *New developments in multiple objective and goal programming* (pp. 15–33). Springer. https://doi.org/10.1007/978-3-642-10354-4_2

Bilkštytė-Skanė, D., & Akstinaite, V. (2024). Strategic organizational changes: Adopting data-driven decisions. *Strategic Change*, *33*(2), 107-116.

Bravo, M., Pla-Santamaria, D., & Garcia-Bernabeu, A. (2010). Portfolio selection from multiple benchmarks: A goal programming approach to an actual case. *Multi-Criteria Decision Analysis, 17*, 155–166. https://doi.org/10.1002/mcda.460

Charnes, A., Cooper, W., & Ferguson, R. (1955). Optimal estimation of executive compensation by linear programming. *Management Science, 1*, 138–151. https://doi.org/10.1287/mnsc.1.2.138

Dash, G., & Kajiji, N. (2014). On multiobjective combinatorial optimization and dynamic interim hedging of efficient portfolios. *International Transactions in Operational Research, 21*, 899–918. https://doi.org/10.1111/itor.12067

Dasha, M., & Hanuman, R. (2015). Goal programming model for working capital management. *Journal of Management and Science, 5*, 7–16.

Fazekas, B., Póta, C. P., & Becsky-Nagy, P. (2024). Accelerate or brake?—The connection of credit gaps and economic disequilibrium. *Strategic Change*, *33*(3), 139-150.

Gerdessen, J., & DeVries, J. (2015). Diet models with linear goal programming: Impact of achievement functions. *European Journal of Clinical Nutrition, 69*, 1272-1278.

Gkillas, K., Tsagkanos, A., & Vortelinos, D. I. (2019). Integration and risk contagion in financial crises: Evidence from international stock markets. *Journal of Business Research, 104*, 350–365. https://doi.org/10.1016/j.jbusres.2019.07.031

Grosse, R. (2017). The global financial crisis - Market misconduct and regulation from a behavioral view. *Research in International Business and Finance, 41*, 387–398. http://dx.doi.org/10.1016/j.ribaf.2017.04.056

Huck, N., Mavoori, H., & Mesly, O. (2020). The rationality of irrationality in times of financial crises. *Economic Modelling, 89*, 337–350. https://doi.org/10.1016/j.econmod.2019.10.033

Ignizio, J. (1985). *Introduction to linear goal programming.* Sage University Paper Series, Quantitative applications in the social sciences, 07-056. Sage Publications, Inc.

Jatuphatwarodom, N., Jones, D. F., & Ouelhadj, D. (2018). A mixed-model multi-objective analysis of strategic supply chain decision support in the Thai silk industry. *Annals of Operations Research, 267*(1), 221-247.

Jones, D. F., & Tamiz, M. (2010). *Practical goal programming*. International Series in Operations Research and Management Science, Springer.

Karmani, M., Uyar, A., & Kuzey, C. (2023). How did European firms adjust their corporate social responsibility investments during the global financial crisis?. *Strategic Change*, *32*(1), 3-11.

Li, C., Huo, M., Li, C., Li, G., & Liu, R. (2023). Economic policy uncertainty and enterprise strategic change: Evidence from China. *Strategic Change*, *32*(4-5), 125-137.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*, 77–91.

Markowitz, H. (1995). *Portfolio selection: Efficient diversification of investments*. 2nd Edition, Blackwell Publishers.

Masri, H. (2015). A multiple stochastic goal programming approach for the agent portfolio selection problem. *Annals of Operations Research, 228*, 1–14. https://doi.org/10.1007/s10479-015-1884-7

Messaoudi, L., Aouni, B., & Rebai, A. (2015). Fuzzy chance-constrained goal programming model for multi-attribute financial portfolio selection. *Annals of Operations Research, 232*, 1–12. https://doi.org/10.1007/s10479-015-1937-y

Pardalos, P., Steponavice, X., & Zilinskas, A. (2012). Pareto set approximation by the method of adjustable weights and successive lexicographic goal programming. *Journal of Optimization Letters, 6*, 665–678. https://doi.org/10.1007/s11590-011-0291-5

Romero, C. (2001). Extended lexicographic goal programming: A unifying approach, *Omega, 29*, 63–71. https://doi.org/10.1016/S0305-0483(00)00026-8

Romero, C. (2004). A general structure of achievement function for a goal programming model. *European Journal of Operational Research, 153*, 675-686.

Salisu, A. A., & Vo, X. V. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *International Review of Financial Analysis, 71*. https://doi.org/10.1016/j.irfa.2020.101546.

Sharpe, W. (1985). *Investments*. 3rd edition, Prentice-Hall Inc.

Spelta, A., Flori, A., Pecora, N., & Pammolli, F. (2021). Financial crisis: Uncovering self-organized patterns and predicting stock markets instability. *Journal of Business Research*, *129*, 736–756. https://doi.org/10.1016/j.jbusres.2019.10.043.

Tamiz M., & Jones D. F. (1997). An example of good modeling practice in goal programming: Means for overcoming incommensurability. In R. Caballero, F. Ruiz, & R. Steuer (Eds.), *Advances in multiple objective and goal programming* (pp. 29–37). Springer.

Tamiz, M., & Azmi, R. A. (2019). Goal programming with extended factors for portfolio selection. *International Transactions in Operational Research, 26*, 2324–2336. https://doi.org/10.1111/itor.12423

Tamiz, M., Azmi, R. A., & Jones, D. F. (2013). On selecting portfolio of international mutual funds using goal programming with extended factors. *European Journal of Operational Research, 226*, 560–576. https://doi.org/10.1016/j.ejor.2012.11.004

Tamiz, M., Jones, D. F. & Romero, C. (1998). Goal programming for decision making: An overview of the current state-of-the-art. *European Journal of Operational Research, 111*, 569–581. https://doi.org/10.1016/S0377-2217(97)00317-2

Zhou, J. (2020). Household stock market participation during the great financial crisis. *The Quarterly Review of Economics and Finance, 75,* 265–275. https://doi.org/10.1016/j.qref.2019.04.008

Zhu, J. (2023). Who are the founders of venture capital-backed initial public offering companies in the United States?. *Strategic Change*, *32*(2-3), 73-84.

Table I: Stocks Data and Corresponding Factors

Stock	Factors		
Variables	Return	Risk	Correlation
X1	0.21%	2.84%	10.30%
X2	0.16%	2.64%	12.20%
X3	0.20%	2.34%	8.33%
X4	-0.09%	3.59%	8.33%
X5	-0.08%	2.52%	0.90%
X6	-0.12%	3.54%	3.77%
X7	0.04%	1.79%	9.12%
X8	0.16%	2.02%	8.21%
X9	0.01%	1.57%	10.30%
X10	0.10%	2.21%	10.14%
X11	0.06%	1.85%	4.87%
X12	0.12%	1.82%	9.17%
X13	-0.03%	1.31%	10.79%
X14	-0.01%	1.67%	14.04%
X15	-0.04%	1.56%	12.31%
Mean	0.05%	2.22%	8.85%
Standard Dev.	0.11%	0.70%	3.44%
Min. Value	-0.12%	1.31%	0.90%
Max. Value	0.21%	3.59%	14.04%

Table II: Various EGP Models and Corresponding “α”

No.	EGP Models	Parameter α
1	EGP1	α = 0.0
2	EGP2	α = 0.2
3	EGP3	α = 0.4
4	EGP4	α = 0.5
5	EGP5	α = 0.6
6	EGP6	α = 0.8
7	EGP7	α = 1.0

Table III: Experiment Key Parameters

	Extended Goal Programming Models (EGP)						
	EGP1	**EGP2**	**EGP3**	**EGP4**	**EGP5**	**EGP6**	**EGP7**
α	0	0.2	0.4	0.5	0.6	0.8	1
D	1.001602317	1.001602317	0.987373155	0.987373155	0.978895765	0.948409775	0.907531922
A	1.175019285	1.140335891	1.104064036	1.084615556	1.064734931	1.00857592	0.907531922

Table IV: Results for the Key Models

Extended Goal Programming Models (EGP)	Portfolio's Return	Portfolio's Risk	Constructed Stocks' Portfolio		
			Number of Portfolio's Constituents (Stocks)	**Stocks Name (Countries)**	**Portfolio's Proportions**
EGP1	0.083%	0.802%	4	HSBC (UK) NTT (Japan) L'Oreal (France) Nestle (Switzerland)	19.34% 20.66% 30.00% 30.00%
EGP2	0.083%	0.802%	4	HSBC (UK) NTT (Japan) L'Oreal (France) Nestle (Switzerland)	19.34% 20.66% 30.00% 30.00%
EGP3	0.081%	1.057%	4	HSBC (UK) L'Oreal (France) Hermes (France) Nestle (Switzerland)	16.51% 30.00% 23.49% 30.00%
EGP4	0.081%	1.057%	4	HSBC (UK) L'Oreal (France) Hermes (France) Nestle (Switzerland)	16.51% 30.00% 23.49% 30.00%
EGP5	0.061%	0.970%	4	HSBC (UK) Sony (Japan) L'Oreal (France) Nestle (Switzerland)	13.42% 26.58% 30.00% 30.00%
EGP6	0.057%	1.228%	5	Amazon (US) HSBC (UK) Sony (Japan) L'Oreal (France) Hermes (France)	03.19% 06.81% 30.00% 30.00% 30.00%
EGP7	0.056%	1.365%	4	Apple (US) Microsoft (US) Amazon (US) Sony (Japan)	30.00% 30.00% 30.00% 10.00%

Table V: Performance Evaluation for the Constructed Portfolios (Portfolios' Risk)

Main Benchmarks			Portfolio Risk Difference [P - B] *						
			EGP1	**EGP2**	**EGP3**	**EGP4**	**EGP5**	**EGP6**	**EGP7**
MSCI World		**Percent Change**	-0.030	-0.030	+0.225	+0.225	+0.138	+0.396	+0.533
Relevant Benchmarks to the Constructed Portfolios	S&P 500	%						+0.270	+0.408
	FTSE 100	%	-0.096	-0.096	+0.160	+0.160	+0.072	+0.330	
	NIKKEI 225	%	-0.442	-0.442			-0.274	-0.016	+0.156
	CAC 40	%	-0.407	-0.407	-0.152	-0.152	-0.239	+0.019	
	SMI	%	-0.054	-0.054	+0.201	+0.201	+0.114		

** P: Constructed portfolio, B: Benchmark portfolio, P-B: constructed portfolio's risk - benchmark portfolio's risk in percentage.*

Table VI: Performance Evaluation for the Constructed Portfolios (Portfolios' Return)

Main Benchmarks			**Portfolio Return Difference [P - B] ***						
			EGP1	**EGP2**	**EGP3**	**EGP4**	**EGP5**	**EGP6**	**EGP7**
MSCI World		**Percent Change**	0.073	0.073	0.071	0.071	0.050	0.046	0.045
Relevant Benchmarks to the Constructed Portfolios	S&P 500	%						0.016	0.015
	FTSE 100	%	0.035	0.035	0.032	0.032	0.012	0.008	
	NIKKEI 225	%	0.105	0.105			0.082	0.078	0.077
	CAC 40	%	0.040	0.040	0.037	0.037	0.017	0.013	
	SMI	%	0.032	0.032	0.029	0.029	0.009		

** P: Constructed portfolio, B: Benchmark portfolio, P-B: constructed portfolio's return - benchmark portfolio's return in percentage.*

Appendix I: Study's Experiments List of Stocks

No.	Country	Stock Name	Stock Variables
1	United States	Apple Inc.	X1
2		Microsoft Corp.	X2
3		Amazon.com Inc.	X3
4	UK	Royal Dutch Shell	X4
5		HSBC Holdings	X5
6		BP	X6
7	Japan	Toyota Motor CORP	X7
8		Sony	X8
9		Nippon Telegraph and Telephone Corp (NTT)	X9
10	France	LVMH Moet Hennessy Louis Vuitton	X10
11		L'Oréal	X11
12		Hermès	X12
13	Switzerland	Nestlé	X13
14		Roche	X14
15		Novartis	X15

Appendix II: General Weighted Goal Programming Model

$$Min \sum_{i=1}^{m} \left(\frac{\alpha_i n_i}{k_i} + \frac{\beta_i p_i}{k_i} \right)$$

Subject to:
$f_i(x) + n_i - p_i = b_i \qquad i = 1, \dots, m$
$x \in C_s$
$x \geq 0, n_i, p_i \geq 0 i = 1, \dots, m$
Where:
n_i is the i^{th} negative deviational variable.
α_i is the weighting factor for negative deviational variable i.
p_i is thei^{th} positive deviational variable.
β_i is the weighting factor for positive deviational variable i.
k_i is the normalising factor for deviational variable i.
x is the vector of the decision variables.
$f_i(x)$ is the i^{th} objective function.
b_i is the i^{th} target value.
C_s is an optional set of hard constraints.

Appendix III: The Normalized Weighted Goal Programming Model:

$$Min\ \left(\frac{\alpha_{RE}\, n_{RE}}{b_{RE}} + \frac{\beta_{RI}\, p_{RI}}{b_{RI}} + \frac{\beta_{CO}\, p_{CO}}{b_{CO}}\right)$$

Subject to:

$$\sum_{j=1}^{15} RE_j X_j + n_{RE} - p_{RE} = b_{RE}$$

$$\sum_{j=1}^{15} RI_j X_j + n_{RI} - p_{RI} = b_{RI}$$

$$\sum_{j=1}^{15} CO_j X_j + n_{CO} - p_{CO} = b_{CO}$$

$$\sum_{j=1}^{15} X_j = 1$$

$X_j \geq 0 j = 1, \ldots, 15$

$All\ negative \wedge positive\ deviations \geq 0$