

Policy-Constrained Portfolio Allocation Using Linear Programming: A Spreadsheet-Based Verification, Sensitivity Analysis, And Mean-Absolute-Deviation Extension

Soumya Gattani¹, Soham Ratnaparkhi², Sparsh Jain³, Vanshika Shah⁴, Vedansh Arora⁵, Vedant Joshi⁶
^{1,2,3,4,5,6}*Bachelor of Science in Finance, NMIMS (ASMSOC), Mumbai, India*

Abstract—Portfolio selection becomes even more complicated when investment policy imposes some constraints on capital, risk, concentration and liquidity. LP model is useful in addressing those types of problems because the imposed restrictions may be stated as linear constraints. Another method for incorporating portfolio risk in the model without specifying the covariance matrix, but maintaining LP nature of the problem is the Konno-Yamazaki mean-absolute-deviation (MAD) method. In this paper, the spreadsheet implementation of the models is developed and feasibility check, duality and sensitivity analysis are used for explaining the optimal portfolio selection. The first model allocates \$10 million portfolio between five assets under the budget, risk-score, equity concentration, liquidity and asset-specific constraints. The annual return for the obtained portfolio is \$934,000, which corresponds to the portfolio yield of 9.34%, with \$3.4 million allocated to growth equities, \$3.1 million to corporate bonds and \$3.5 million to government securities. Budget, risk score and maximum 35% weight in government securities are binding constraints, with shadow prices of \$0.032 per additional dollar of capital and \$0.012 per additional risk point correspondingly. Moreover, the infeasibility of an earlier proposed allocation of \$970,000 that exceeds the risk ceiling by 4 million points is identified. An increase. Increasing the risk ceiling from 50 million to 55 million points increases the optimum to \$985,000, although the original shadow price cannot be applied throughout that interval. A second exercise applies the linearised MAD formulation to twelve months of synthetic returns for four assets and compares its portfolios with Markowitz mean-variance solutions. At the same target return, the two approaches can produce materially different allocations, with a maximum weight-distance of 25 percentage points in the reported cases. Because the data are synthetic and the exercise is in-sample, the findings are methodological rather than evidence of investment

performance. The workbook is intended as an auditable academic implementation rather than as investment advice.

I. INTRODUCTION

Investment management is the core decision problem of allocating capital among asset classes within regulatory and policy limits. Markowitz's mean-variance framework (1952) formalized the risk-return trade-off but requires a dense covariance matrix and quadratic programming, which becomes cumbersome with an increasing number of assets. Konno and Yamazaki (1991) proposed mean-absolute deviation (MAD) as a risk measure that leads to a linear program and does not require estimation of covariance. Later work has extended linear and LP-solvable portfolio models to transaction costs, cardinality constraints and robust formulations (Konno & Wijayanayake, 2001; Mansini et al., 2003, 2014; Bertsimas & Sim, 2004). Introductory treatments of portfolio LPs usually rely on stylised parameters and seldom show how binding constraints and dual values explain the solution. Accessible implementations of MAD that anyone can reproduce and audit without programming are also scarce.

This paper addresses that gap in a limited way. It makes three contributions:

- A fully verified five-asset allocation LP, with a closed-form primal-dual optimality proof and a sensitivity analysis in which shadow prices show which policy limits drive returns;
- A reproducible Excel implementation of the linearised MAD model and of Markowitz mean-variance optimisation on the same data, with the Solver set-up documented; and

- A transparent record of an infeasible earlier result, which shows why every reported optimum should be checked for feasibility.

The paper does not claim a new optimisation model, and it does not test either model on real market data (see Section 8).

II. BACKGROUND

Linear programming, formalised by Dantzig (1963), maximises a linear objective over a polyhedron defined by linear constraints. Every LP has a dual, and at optimum the primal and dual objective values coincide (strong duality). The dual variables, also called shadow_prices, correspond to the marginal value of relaxing each constraint and form the basis for sensitivity analysis (Vanderbei, 2020).

In portfolio theory, Markowitz (1952, 1959) measures risk by the variance of portfolio return, so the resulting optimization model is quadratic. Konno (1990) and Konno and Yamazaki (1991) replaced the variance by the mean absolute deviation, which is linearizable with one auxiliary variable per period, so that large problems can be solved by LP.

Mansini et al. (2014) review twenty years of LP-based portfolio optimization, and Kolm et al. (2014) review sixty years of portfolio optimization. The practical challenges of estimation error and transaction costs are considered. Bertsimas and Sim (2004) demonstrate that robust formulations with a bounded "budget of uncertainty" can remain linear. Spreadsheet solvers have been used for such models for decades (Fylstra et al., 1998).

III. LITERATURE REVIEW

Portfolio optimization has developed from traditional risk-return models into a broader set of optimization approaches that incorporate alternative risk measures, computational efficiency, and robustness to uncertain inputs.

This study builds its theoretical foundation around five key research papers that trace this development from the classical mean–variance framework to linear programming and robust portfolio optimization.

3.1 Markowitz (1952): Mean–Variance Portfolio Selection

Markowitz (1952) established the foundation of modern portfolio theory by introducing the mean–variance framework for portfolio selection. The model evaluates portfolios by considering two central characteristics: expected return and the variance of portfolio returns as a measure of risk. Investors are assumed to prefer higher expected returns while seeking to control the level of risk undertaken.

The importance of Markowitz's work lies in its formal treatment of diversification. Rather than evaluating securities independently, the framework considers how the returns of different assets interact through their covariance. This allows investors to construct portfolios in which diversification can reduce overall portfolio risk.

However, the classical mean–variance model is a quadratic optimization problem because portfolio variance depends on the covariance matrix. This can make the model computationally more demanding and sensitive to estimation errors in expected returns and covariances. These limitations provided motivation for researchers to investigate alternative formulations that could be solved using linear programming.

However, the traditional mean-variance framework represents a quadratic program since the variance of the portfolio depends on the covariance matrix. Such a model could be computationally more difficult and could be prone to estimation errors in the expected returns and covariances. The above problems prompted scholars to explore other models that would be amenable to linear programming solutions.

3.2 Sharpe (1971): Portfolio Analysis by Means of Linear Programming

In his study of portfolio analysis by means of linear programming, Sharpe (1971) showed that portfolio construction can be performed without being constrained by the quadratic form inherent in the Markowitz model.

In this case, one of the advantages associated with applying linear programming is that the objective function and the constraints can be modeled as linear functions.

As far as the current research project is concerned, Sharpe's contribution is particularly important because the suggested portfolio model relies on linear

programming for capital allocation among the assets taking into account investment constraints.

3.3 Konno and Yamazaki (1991): Mean Absolute Deviation Portfolio Optimization

Konno and Yamazaki (1991) suggested a mean-absolute deviation (MAD) model as another portfolio optimization technique which replaces the variance as the measure of risk. Instead of trying to minimize the variance, this model focuses on minimizing the absolute deviations of portfolio returns from their expected value.

One of the main advantages of the MAD model is that it can be written as a linear programming problem. It gives the opportunity to avoid the more complex quadratic programming problem which is typical of the Markowitz model. It keeps the core idea of balancing the expected return and risk but makes it possible to solve the problem through linear programming.

This article is especially relevant to the current research because the report uses the linear programming model with the MAD extension.

3.4 Bertsimas and Sim (2004): Robust Optimization

Bertsimas and Sim (2004) have studied robust optimization as an approach to coping with uncertainties in optimization problems. According to their framework, the uncertainty in the problem is associated with parameters in optimization models that are often not known completely. The framework aims at developing a technique that will limit the impact of adverse deviations in these parameters.

Robustness is applicable to portfolio optimization due to the fact that estimates of financial parameters such as expected returns and risks are based on assumptions or on historical data. Even small variations in these parameters may influence the optimal portfolio. Robust optimization helps to explore the sensitivity of the optimal portfolio to uncertainties in its parameters.

In the current research, the robustness approach validates the application of sensitivity analysis. As opposed to the idea of finding a single optimal portfolio, the research examines the impacts of changes in the policy constraints on the optimal portfolio.

3.5 Mansini, Ogryczak and Speranza (2014): Linear and Mixed Integer Programming for Portfolio Optimization

In their work, Mansini, Ogryczak and Speranza (2014) considered the applicability of linear and mixed integer programming methods to portfolio optimization. This paper shows how the process of portfolio optimization can include real-life investment constraints into mathematical programming problems. The important part of the discussed stream of research is the inclusion of real-life constraints into the portfolio optimization model. Such constraints can refer to the limitations regarding minimum/maximum shares, diversification, transactional issues, or any other constraints imposed by the investor. Thus, mathematical programming is a way to systematically take such constraints into account in the process of portfolio optimization.

This research is strongly connected to the current paper, since the suggested model includes investment policy constraints into the optimization problem. Specifically, the research applies linear programming to the portfolio of five assets and analyzes the solution obtained through optimization by spreadsheets.

3.6 Synthesis of the Literature

The literature review reveals the evolution of portfolio optimization from classical risk-reward analysis to practical and computationally efficient portfolio optimization. The overall contribution of these papers reflects the shift from the classical mean-variance portfolio analysis towards linear, robust and constrained portfolio optimization. Markowitz offers the theoretical basis for analyzing the risk-reward ratio, while Sharpe and Konno and Yamazaki explain how portfolio optimization can be performed by using linear programming. The work of Bertsimas and Sim offers the concept of uncertainty, while the study by Mansini et al. covers the broader use of mathematical programming.

Research Gap

Whereas existing literature does have many theoretical models for portfolio optimization, a practical model which can implement policy constraints, linear programming, spreadsheet analysis, and sensitivity analysis all together needs to be constructed.

The current research fulfills this gap through a model for a five-asset constrained policy portfolio and

implementing it in a spreadsheet linear programming model framework. After solving this problem, independent verification and then sensitivity analysis of some important constraints are performed. This framework is further extended using a mean absolute deviation approach and compared with the Markowitz type mean-variance framework using example numbers.

Thus, this paper does not bring in any new theories related to portfolio optimization, but demonstrates the application of optimization principles already known theoretically.

IV. MODELS AND METHODS

4.1 Policy-constrained allocation LP

A manager allocates $B = \$10,000,000$ across five asset classes. Let x_i be the dollar amount in asset i , r_i its expected annual return and w_i its risk score on a 1–10 scale. The model is:

maximise $Z = \sum r_i x_i$

subject to $\sum x_i \leq B$; $\sum w_i x_i \leq 5B$; $x_1 + x_2 \leq 0.50B$; $x_4 + x_5 \geq 0.25B$; $x_i \leq 0.35B$; $x_i \geq 0$.

The second constraint caps the capital-weighted average risk score at 5, so the risk ceiling is $5B = 50,000,000$ risk points. The inputs are stylised parameters, not market data (Table 1).

Table 1: Input Parameters (Illustrative).

Asset class	Variable	Expected return r_i	Risk score w_i
Growth equities	x_1	14%	9
Dividend equities	x_2	10%	6
Corporate bonds	x_3	8%	4
Government securities	x_4	6%	2
Money market	x_5	4%	1

The model was solved with the HiGHS LP solver (Huangfu & Hall, 2018), and the stored optimum is reproducible in Excel Solver using the Simplex LP method with “make unconstrained variables non-negative” ticked. Solver settings are listed in Appendix A.

4.2 Verification by feasibility and duality

A reported optimum is accepted only if it passes two checks that are built into the workbook as live

formulas. First, a feasibility check evaluates every constraint and flags violations. Second, the optimum is proved by solving the binding constraints in closed form and constructing a dual solution whose objective equals the primal objective. If the primal solution is feasible, the dual solution is feasible, and the duality gap is zero, then no better allocation exists.

4.3 Konno–Yamazaki MAD model

Given returns r_{jt} for assets $j = 1, \dots, n$ in periods $t = 1, \dots, T$ with means $\bar{r}_j$, the MAD of portfolio weights x is $(1/T) \sum_t |\sum_j (r_{jt} - \bar{r}_j) x_j|$. Introducing $y_t \geq |d_t|$, where $d_t = \sum_j (r_{jt} - \bar{r}_j) x_j$, gives the LP:

minimise $(1/T) \sum_t y_t$

subject to $y_t + d_t \geq 0$, $y_t - d_t \geq 0$, $\sum_j \bar{r}_j x_j \geq \rho$, $\sum_j x_j = 1$, $0 \leq x_j \leq M$.

Here ρ is the target minimum return and M an upper bound on any single weight. The workbook contains 4 weights and 12 auxiliary variables. Excel Solver allows 200 changing cells, so the number of assets plus the number of periods must not exceed 200.

4.4 Markowitz comparator

The comparator minimises the portfolio variance $x^T \Sigma x$ subject to the same target-return, budget and bound constraints, where Σ is the sample covariance matrix (divisor $T - 1$). Markowitz weights in the workbook were obtained with an SLSQP quadratic solver, and a single-run block is provided for Excel Solver with the GRG Nonlinear method.

V. RESULTS: ALLOCATION LP

5.1 Optimal allocation

Table 2: Optimal Allocation ($B = \$10,000,000$).

Asset class	Allocation (\$)	Weight	Annual return (\$)	Risk points
Growth equities (x_1)	3,400,000	34%	476,000	30,600,000
Dividend equities (x_2)	0	0%	0	0
Corporate bonds (x_3)	3,100,000	31%	248,000	12,400,000
Government securities (x_4)	3,500,000	35%	210,000	7,000,000

Asset class	Allocation (\$)	Weight	Annual return (\$)	Risk points
Money market (x_5)	0	0%	0	0
Total	10,000,000	100%	934,000	50,000,000

The optimal annual return is $Z^* = \$934,000$, a portfolio yield of 9.34%. Three constraints bind: the capital budget, the risk ceiling (50,000,000 of 50,000,000 points) and the single-asset cap on government securities (35%). The equity cap (3.4 million against 5.0 million) and the liquidity floor (3.5 million against 2.5 million) have slack of \$1.6 million and \$1.0 million respectively and do not affect the optimum.

5.2 Proof of optimality

Fixing x_4 at its cap of 3.5 million leaves 6.5 million of budget and 43 million risk points for x_1 and x_3 . Solving $x_1 + x_3 = 6.5$ and $9x_1 + 4x_3 = 43$ gives $x_1 = 3.4$ and $x_3 = 3.1$ million, matching the solver output. The dual prices follow from the two basic variables: $y_R = (r_1 - r_3)/(w_1 - w_3) = (0.14 - 0.08)/(9 - 4) = 0.012$ per risk point, and $y_B = r_3 - w_3 y_R = 0.08 - 4(0.012) = 0.032$ per dollar.

The reduced costs $d_j = r_j - y_B - w_j y_R$ are -0.004 for x_2 , $+0.004$ for x_4 (at its upper bound) and -0.004 for x_5 , all with the signs required for optimality. The dual objective is $0.032(10,000,000) + 0.012(50,000,000) + 0.004(3,500,000) = 934,000$, which equals the primal objective, so the duality gap is zero.

5.3 Why dividend equities are excluded

Dividend equities offer a 10% return at risk score 6. A mix of growth equities and bonds reaches the same average risk with a higher return, and the reduced cost of -0.004 quantifies the loss: each dollar moved into x_2 or x_5 lowers the annual return by \$0.004. Conversely, each extra dollar of room under the government-securities cap would raise the return by \$0.004.

5.4 An infeasible earlier result

An earlier draft of this analysis reported an allocation of (3.0, 2.0, 2.5, 2.5, 0) million dollars with an annual return of \$970,000. This allocation uses $27 + 12 + 10 + 5 = 54$ million risk points, exceeding the ceiling of 50 million by 4 million. It is therefore infeasible and cannot be the optimum; the \$970,000 figure is higher than the true optimum only because the risk constraint is violated. The workbook retains this check for transparency. The episode shows why reported optima should be verified by feasibility and duality checks rather than by the objective value alone.

VI. RESULTS: SENSITIVITY ANALYSIS

The shadow prices imply that each additional risk point raises the optimum by \$0.012 and each additional dollar of capital by \$0.032, but only while the optimal basis is unchanged. The allowable range is [48,000,000; 50,500,000] risk points for the risk ceiling and [9,875,000; 10,222,222] dollars for the budget. Outside these ranges the basis changes, and the linear prediction is no longer exact. Table 3 compares the shadow-price prediction with the re-solved optimum.

Table 3: What-If Scenarios: Re-Solved Optimum Versus Shadow-Price Prediction.

Parameter	New value	Re-solved Z^* (\$)	Prediction (\$)	Error (\$)	Inside range?
Risk ceiling	46,000,000	885,000	886,000	-1,000	No
Risk ceiling	48,000,000	910,000	910,000	0	Yes
Risk ceiling	49,000,000	922,000	922,000	0	Yes
Risk ceiling	50,500,000	940,000	940,000	0	Yes
Risk ceiling	52,000,000	955,000	958,000	-3,000	No
Risk ceiling	55,000,000	985,000	994,000	-9,000	No
Capital budget	9,500,000	915,000	918,000	-3,000	No
Capital budget	9,875,000	930,000	930,000	0	Yes

Parameter	New value	Re-solved Z^* (\$)	Prediction (\$)	Error (\$)	Inside range?
Capital budget	10,222,000	941,104	941,104	0	Yes
Capital budget	10,500,000	948,750	950,000	-1,250	No
Capital budget	11,000,000	962,500	966,000	-3,500	No

Within the valid ranges the prediction error is zero in every scenario. Outside them the linear prediction overstates the gain from relaxing a constraint (and understates the loss from tightening it), because the optimal basis changes and another constraint becomes binding (for example, the 35% single-asset cap on growth equities when the risk ceiling is raised). For example, raising the risk ceiling to 55 million points produces \$985,000 against a linear prediction of \$994,000. Figure 1 illustrates this concavity. Relaxing the risk ceiling from 50 to 55 million points raises the optimum by 5.5% (from \$934,000 to \$985,000); tightening it to 40 million points lowers it to \$810,000.

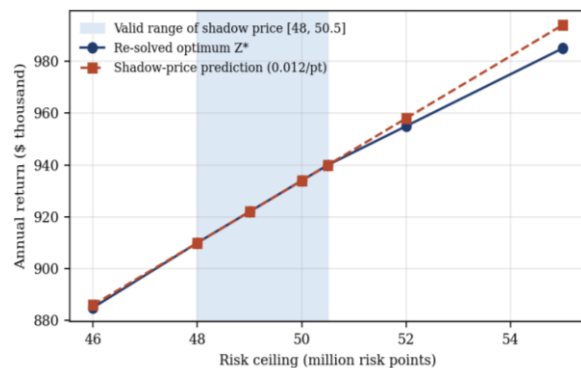


Figure 1: Optimal annual return as a function of the risk ceiling. The shadow-price line is exact only inside the shaded range.

VII. RESULTS: MAD AND MARKOWITZ ON A SYNTHETIC DATA SET

To demonstrate the mechanics of the MAD model, the workbook uses 12 months of synthetic returns for four assets. These are invented numbers, constructed so that the arithmetic can be followed by hand.

They are not market data, and 12 observations cannot support any empirical claim. Monthly mean returns are 1.10%, 1.45%, 0.65% and 0.50%, and standard deviations are 3.13%, 5.01%, 0.94% and 1.67% for assets 1 to 4.

7.1 MAD-optimal portfolios

With a target return of $\rho = 0.9\%$ per month and a weight cap of $M = 0.5$, the MAD-optimal weights are (0.418, 0.145, 0.074, 0.363), with a MAD of 1.040%. An equal-weight portfolio earns a comparable 0.925% per month but has a MAD of 1.209%.

Table 4 shows the MAD-efficient portfolios for several targets. The frontier rises steeply for $\rho > 1.0$ because asset 1 reaches its cap of 0.5 and the model must move into the riskier asset 2.

Table 4: Mad-Optimal Portfolios by Target Return (Synthetic Data; % Per Month).

Target ρ	x_1	x_2	x_3	x_4	Return	MAD
0.7	0.083	0.080	0.500	0.337	0.70	0.556
0.8	0.225	0.118	0.358	0.299	0.80	0.688
0.9	0.418	0.145	0.074	0.363	0.90	1.040
1.0	0.500	0.210	0.000	0.290	1.00	1.458
1.1	0.500	0.315	0.000	0.185	1.10	1.905
1.2	0.500	0.421	0.000	0.079	1.20	2.352
Equal weight	0.250	0.250	0.250	0.250	0.925	1.209

7.2 Comparison with Markowitz

By construction, at each target return the Markowitz portfolio has the smallest standard deviation and the MAD-optimal portfolio has the smallest MAD. The question is how much the two risk measures disagree on a given data set.

Table 5 reports the gaps. The largest disagreement is at $\rho = 0.9$, where the MAD-optimal portfolio has a standard deviation 6.4% higher (1.454% against 1.367%) but a MAD 4.4% lower (1.040% against 1.088%), and where 25 percentage points of the portfolio are allocated differently. At the highest target (1.2%) the cap forces both models to the same portfolio.

Table 5: Mad-Optimal Versus Markowitz Portfolios (Synthetic Data; % Per Month).

Target ρ	SD: Markowitz	SD: MAD-opt	MAD: Markowitz	MAD: MAD-opt	Weight distance
0.7	0.652	0.664	0.560	0.556	0.030
0.8	0.950	0.955	0.709	0.688	0.052
0.9	1.367	1.454	1.088	1.040	0.254
1.0	1.822	1.874	1.501	1.458	0.207
1.1	2.293	2.295	1.914	1.905	0.046
1.2	2.784	2.784	2.352	2.352	0.000

Weight distance = $\frac{1}{2} \sum |\Delta x_j|$, the share of the portfolio allocated differently.

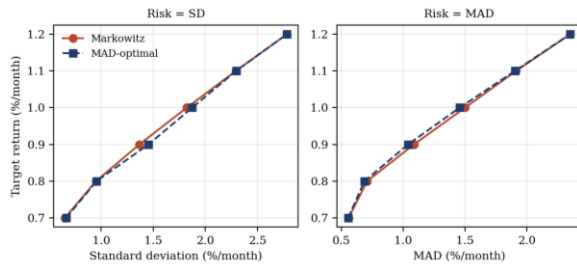


Figure 2: Efficient frontiers on the synthetic data, measured by standard deviation (left) and MAD (right).

These differences come from a 12-month sample with four assets and are in-sample. They show how the models work and where they diverge, and they should not be generalised to real markets.

VIII. LIMITATIONS AND PLANNED EMPIRICAL EXTENSION

- No real data. The LP parameters are assumed, and the MAD and Markowitz comparison uses synthetic returns. No out-of-sample or benchmark evidence is provided.
- Crude risk proxy. The 1–10 risk scores are linear and subjective, and the LP has no covariance structure, so diversification effects are ignored.
- Forecast error and costs. Historical or assumed returns are treated as certain forecasts, and transaction costs, taxes and rebalancing are omitted.
- Scope of extensions. Mixed-integer (cardinality), goal-programming and robust formulations are not implemented here.

The accompanying workbook contains a template for the next step. It accepts 61 month-end adjusted prices for up to eight assets, uses 48 months for training and

12 for testing, and runs MAD and Markowitz Solver models with out-of-sample evaluation. Because the model sizes (8 weights + 48 auxiliary variables = 56 changing cells) are well within Solver's limit, the exercise is feasible in Excel. A follow-up study using Indian equity, gold and debt index data would report out-of-sample return, risk, drawdown and turnover for both models.

IX. CONCLUSION

In this paper, linear programming techniques have been demonstrated on their application to portfolio selection problems with real-life policy and investment constraints. Using a portfolio of five assets, the model has given a systematic way to allocate investments in order to meet certain criteria of investment constraints in addition to meeting the necessary portfolio composition requirements.

It is important to note here that through sensitivity analysis, one can get valuable information regarding an optimal portfolio in terms of the constraints that affect the solution of investment problem the most. It is thus recommended that the portfolio should not be treated in a static manner but rather in a dynamic fashion. The mean absolute deviation extension contributes an additional aspect to the analysis by using absolute deviation instead of variance as the measure of risk. It is used to show how linear programming can incorporate other methods of measuring risk, yet remain computationally straightforward. The analysis also reveals that a different definition of risk could yield different portfolio allocations and results.

In conclusion, this research has shown that policy constrained linear programming can be a very effective tool for constructing portfolios of assets. Being combined with spreadsheet verification,

sensitivity analysis and alternative risk measures, policy constrained linear programming becomes especially valuable in understanding how mathematical programming can help to make investment decisions in practice. Although the results of this study are based on hypothetical data and therefore cannot reflect the behavior of an actual portfolio, this method forms a solid basis for further research with real data, transaction costs and other elements taken into account.

Declarations

Use of AI tools. Generative AI (Claude, Anthropic) was used to assist with model checking, drafting and language editing. The authors reviewed all content and take full responsibility for it.

Data and code availability. The Excel workbook (Portfolio_LPP_Excel_Model_v2.xlsx) contains all inputs, formulas and Solver settings. No real market data were used.

Disclaimer. This paper is for academic purposes only and does not constitute investment advice.

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APPENDIX A: EXCEL SOLVER SETTINGS

Table A1: Solver parameters for the three models in the workbook.

Item	Allocation LP (LPP_Model)	MAD (MAD_Model)	Markowitz (MAD_vs_Markowitz)
Objective	Max \$C\$22	Min \$B\$30	Min \$B\$27
Changing cells	\$C\$14: \$C\$18	\$B\$26: \$E\$26, \$L\$10: \$L\$21	\$B\$25: \$E\$25
Constraints	Budget $\leq$; risk $\leq$; equity cap $\leq$; liquidity $\geq$; $x_i \leq 35\% B$	M10:N21 ≥ 0 ; return $\geq \rho$; $\Sigma x = 1$; $x_j \leq M$	$\Sigma x = 1$; return $\geq \rho$; $x_j \leq M$
Non-negative	Checked	Checked	Checked
Method	Simplex LP	Simplex LP	GRG Nonlinear