Returns, Risk, and Health Impact: A DALY Weighted Portfolio Model

By

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ABSTRACT

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Impact investors in global health often want two things at once: a reasonable financial return and large health gains. Standard portfolio models focus on expected return and risk, but they ignore health outcomes. This paper builds a simple simulation to show how health impact can be brought directly into a portfolio problem using disability adjusted life years (DALYs) as the outcome metric.

I construct a universe of nine stylized global health programs, including childhood vaccines, malaria nets, HIV treatment, and chronic disease screening. Each program is assigned a plausible expected financial return, volatility, and DALYs averted per \$1 million of capital. Using these inputs, I compare three portfolio rules: a standard mean variance portfolio, an impact weighted utility portfolio, and a family of portfolios that impose a minimum DALY floor.

The results show clear tradeoffs. The pure mean variance portfolio delivers an expected return of about 9.3 percent with a standard deviation of 5.3 percent, but only around 1,450 DALYs per \$1 million. An impact weighted portfolio with a modest impact weight yields a lower expected return of about 6.8 percent and a standard deviation of 4.4 percent, but more than 5,100 DALYs per \$1 million. Adding DALY floors traces out an impact efficient frontier where investors can trade a small drop in return for large gains in health impact. The simulated model is simple by design, but it gives a clear structure for thinking about health-weighted portfolio choice and for motivating empirical work with real global health cost effectiveness data.

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Chapter 1

Introduction

Impact investing tries to link financial outcomes to real world change. In global health, that change is often measured in lives saved, illness avoided, or quality of life gained. At the same time, most of the tools used to build portfolios for investors still focus only on expected return and risk.

This paper asks a simple question: what happens to an investor's optimal portfolio if health impact is treated as a first class objective instead of an afterthought. To keep the problem clean and transparent, I work with a simulated dataset of global health programs rather than firm level ESG scores. Each program is described by three quantities:

- expected financial return,
- financial risk (variance of returns),
- DALY (Disability adjusted life years)[1] averted per $1 million invested.

Using this synthetic universe, I compare three ways of using these inputs in a portfolio model:

[1]A DALY is a summary health metric that combines years of life lost due to early death with years lived with disability, and was formalized in the Global Burden of Disease studies led by Murray and Lopez (1996).

1. a standard mean variance portfolio that ignores health impact,
2. an impact weighted utility portfolio that adds DALYs as a positive term in the objective,
3. portfolios that impose a minimum DALY floor and then choose the best remaining mean variance portfolio.

The goal is not to estimate true cost effectiveness for any real program. Instead, the goal is to show how health impact changes the shape of the efficient frontier and how investors can think about tradeoffs between return, risk, and DALYs in a unified way.

This thesis makes a small but concrete contribution to this literature. It takes the idea of an ESG-style efficient frontier and rebuilds it in a health-specific setting where the impact term is DALYs per dollar instead of a composite ESG score. It then compares two ways of bringing DALYs into portfolio choice: a soft approach based on an impact term in the utility function and a hard approach based on minimum DALY floors. The simulation results show how these two approaches pick different portfolios and trace out a clear frontier between financial return and health impact.

This creates a direct tension in the model. The programs that give strong health gains are not always the ones with the highest financial return. That tradeoff is what the thesis studies.

The rest of the thesis is organized as follows. Chapter 2 reviews the relevant literature on impact investing, ESG efficient frontiers, and health cost effectiveness. Chapter 3 presents the model. Chapter 4 describes the simulated data. Chapter 5 explains the numerical method. Chapter 6 reports the results. Chapter 7 discusses implications and limitations. Chapter 8 concludes.

Chapter 2

Literature Review

This project sits at the intersection of three literatures: modern portfolio theory, ESG and impact investing, and global health cost effectiveness.

On the finance side, the starting point is the mean variance framework, where investors choose portfolio weights to maximize expected return for a given level of risk or, equivalently, to maximize a quadratic utility function in return and variance. Recent work extends this framework to include nonfinancial attributes such as environmental, social, and governance scores. Pedersen, Fitzgibbons, and Pomorski [8] show how to build an ESG efficient frontier by treating ESG scores as a third dimension alongside risk and return, and they show that investors can trace out tradeoffs between financial performance and ESG quality.

A second branch of the literature studies how to price assets when investors care about ESG. Lauria et al. [6] develop an asset pricing model where investors derive utility from holding ESG valued assets and where the market prices these preferences. Their setting is closer to public equity markets, but the idea that investors have preferences over impact as well as return is central here.

On the global health side, the main tools are cost effectiveness analysis[1] and

[1] Cost-effectiveness analysis compares the costs of an intervention to the health gains it produces, often measured in DALYs or QALYs. It is widely used in global health policy and WHO evaluation guidelines.

DALYs. DALYs combine years of life lost due to early death with years lived with disability. The DALY framework originates from the Global Burden of Disease work by Murray and Lopez [7], later expanded by the GBD Collaborators [1]. These studies established DALYs as a standard way to combine premature mortality and disability into a single measure of health burden. Cost-effectiveness analysis in global health builds on these foundations, with WHO providing formal guidance on how to value health interventions [2].

Large-scale reviews such as Disease Control Priorities (DCP3) [5] highlight how different health programs vary widely in their cost per DALY averted, and organizations such as GiveWell regularly publish empirical DALY-per-dollar estimates for interventions including vaccines, malaria nets, and HIV treatment [3]. Policy reports by organizations such as the World Health Organization and work summarized in case studies like LeapFrog Investments and UN PRI [4] show how investors and philanthropies can use DALYs to value health programs.

Most of the existing work either treats impact in qualitative terms or focuses on ESG scores in public equity markets. There is much less work that uses DALYs directly as the impact metric in a quantitative portfolio model. This is the gap that motivates the simple framework developed in the next chapters. This thesis connects these pieces by building a small mean variance model where the "impact" term is explicitly defined as DALYs per dollar, instead of a composite ESG score. The structure is closest in spirit to the ESG efficient frontier, but with a health specific outcome measure and portfolio rules that impose minimum health impact floors.

Chapter 3

Model

3.1 Portfolio setup

Consider a universe of n health investments. Let

- $\mu \in R^n$ be the vector of expected returns,
- $\Sigma \in R^{n\times n}$ be the covariance matrix of returns,
- $I \in R^n$ be the vector of DALYs averted per $1 million invested,
- $w \in R^n$ be the vector of portfolio weights.

Weights satisfy the usual budget constraint and non-negativity:

$$\sum_{i=1}^{n} w_i = 1, \qquad w_i \geq 0 \text{ for all } i.$$

The portfolio return R_p, variance $\mathrm{Var}(R_p)$, and DALYs I_p are

$$E[R_p] = \mu^\top w, \tag{3.1}$$

$$\mathrm{Var}(R_p) = w^\top \Sigma w, \tag{3.2}$$

$$I_p = I^\top w. \tag{3.3}$$

Throughout the thesis, expected returns are annual and measured in decimal form, variances are annual return variances, and DALYs are measured per $1 million of capital. All reported portfolio outcomes use these same units, so that, for example, a value of 0.07 for expected return means 7 percent per year and a value of 4,500 for I_p means 4,500 DALYs per $1 million invested.

3.2 Mean variance utility with impact

A standard quadratic utility for a risk averse investor is

$$U_{\mathrm{MV}}(w) = E[R_p] - \lambda \,\mathrm{Var}(R_p), \tag{3.4}$$

where $\lambda > 0$ is a risk aversion parameter.

To incorporate health impact directly, I add a linear term in DALYs:

$$U_{\mathrm{IMP}}(w) = E[R_p] - \lambda \,\mathrm{Var}(R_p) + \beta^{1} \, I_p, \tag{3.5}$$

where $\beta \geq 0$ measures how much utility the investor assigns to one additional DALY per $1 million invested. When $\beta = 0$ this collapses to standard mean variance utility.

3.3 Optimization problems

I study three related optimization problems.

[1] β tells us how much the investor values one extra DALY per $1 million. When $\beta = 0$, the model becomes a regular mean variance problem.

3.3.1 Pure mean variance portfolio

The first problem ignores health impact and chooses weights to maximize standard mean variance utility:

$$\max_{w} \quad \mu^\top w - \lambda w^\top \Sigma w \quad \text{subject to} \quad \sum_i w_i = 1,\ w_i \geq 0. \tag{3.6}$$

3.3.2 Impact weighted utility portfolio

The second problem uses the impact weighted utility:

$$\max_{w} \quad \mu^\top w - \lambda w^\top \Sigma w + \beta I^\top w \quad \text{subject to} \quad \sum_i w_i = 1,\ w_i \geq 0. \tag{3.7}$$

For fixed λ, increasing β shifts the solution toward high DALY programs.

3.3.3 DALY floor portfolios

The third problem keeps the standard mean variance objective but imposes a hard floor[2] on DALYs:

$$\max_{w} \quad \mu^\top w - \lambda w^\top \Sigma w \quad \text{subject to} \quad \sum_i w_i = 1,\ w_i \geq 0,\ I^\top w \geq \bar{I}, \tag{3.8}$$

where $\bar{I}$ is a required minimum level of DALYs per \$1 million. Varying $\bar{I}$ traces out an impact efficient frontier.

[2] A DALY floor sets a minimum level of health impact the portfolio must reach. This makes impact a strict requirement instead of a soft preference.

Chapter 4

Data

4.1 Simulated health programs

The empirical part of the thesis uses synthetic data for nine stylized global health programs. Each program is meant to capture the broad profile of a real intervention but the numbers are not estimates for any specific country.

The nine programs are:

- Childhood vaccines
- Maternal health packages
- HIV treatment programs
- Malaria bed net distribution
- Hypertension screening
- Diabetes screening
- Cancer screening
- Telemedicine platforms

- Digital mental health apps

For each program I assign:

- an expected annual financial return,
- a return volatility,
- DALYs averted per $1 million of capital.

Table 4.1 summarizes these assumptions.

Table 4.1: Simulated expected return, risk, and DALYs per $1 million for nine health investments.

Program	Expected return	Volatility	DALYs per $1M
Childhood vaccines	0.060	0.060	6500
Maternal health	0.070	0.080	3000
HIV treatment	0.075	0.100	2500
Malaria nets	0.080	0.090	4000
Hypertension screening	0.085	0.110	1200
Diabetes screening	0.090	0.120	900
Cancer screening	0.095	0.130	1400
Telemedicine	0.100	0.140	700
Mental health app	0.105	0.160	600

The DALY values assigned to each program are scaled to match the broad patterns found in global cost-effectiveness research. For example, GiveWell estimates that malaria prevention and childhood immunization often avert DALYs at far lower cost than chronic disease screening or digital health interventions [3]. DCP3 similarly documents that many preventive and maternal-child health interventions occupy the extreme high-value region of the cost-effectiveness distribution [5].

The purpose here is not to reproduce exact empirical estimates from any one source, but to create a numerical landscape that reflects these well-established gradients in cost-effectiveness. Using stylized DALY levels that differ by factors of three or four mirrors the spreads found in WHO and GBD analyses [2, 1].

4.2 Covariance structure

To keep the model simple and transparent, I assume that returns are uncorrelated across programs and build the covariance matrix from the volatilities:

$$\Sigma = \mathrm{diag}(\sigma_1^2, \ldots, \sigma_n^2).$$

This choice allows the focus to stay on the tradeoff between return and DALYs rather than on fine details of return comovement.

4.3 Modeling assumptions and scenario design

The simulated scenario is designed to be simple enough to work through by hand, but rich enough to show meaningful tradeoffs between return and health impact. The choices for program returns, volatilities, and DALYs per $1 million follow three basic principles.

First, the expected returns are set to span a range from 6 percent to a little above 10 percent. This range is meant to reflect the idea that some global health investments look more like concessionary or blended finance opportunities, while others resemble higher return private or quasi-commercial ventures. The exact levels are not meant to match any specific fund or asset class but to give a spread large enough to matter for portfolio choice.

Second, the DALYs per $1 million are chosen so that a few programs, such as childhood vaccines and malaria nets, clearly dominate the others in terms of health impact per dollar. This matches the broad finding from global health cost-effectiveness work that some interventions deliver much larger health gains per dollar than others. The values used here are stylized and do not replicate any single setting, but they are scaled so that moving the portfolio toward these interventions can raise DALYs per

$1 million by a factor of three or four.

Third, I assume zero correlations across program returns and build the covariance matrix as a diagonal matrix. This removes the effect of return comovement and keeps the focus on the tradeoff between financial return and DALYs. In practice, correlations across health investments could matter a great deal, especially if they are exposed to the same countries or funding cycles, but modeling those details lies outside the scope of this first simulation.

On the preference side, the risk aversion parameter is fixed at $\lambda = 3.0$, which produces portfolios with a reasonable amount of diversification given the return and volatility inputs. The impact weight β is chosen from a small grid to generate cases where impact has a visible effect on the optimal portfolio without driving all weight into a single high-DALY program. The goal is not to estimate a realistic value of β for any investor, but to illustrate how different values of β move the solution along an impact-return frontier.

4.4 Visual summary of simulated programs

Figure 4.1 plots expected return against DALYs per $1 million for the nine programs. Childhood vaccines and malaria nets sit in the top part of the plot, with much higher DALYs per dollar than most of the other options. Chronic disease screening, telemedicine, and mental health apps sit closer to the bottom, with higher expected returns but much lower DALYs per dollar.

Figure 4.2 plots volatility against expected return. As expected, programs with higher expected returns generally come with higher risk. In the simulated universe, the programs that look attractive on pure financial grounds are not the same ones that look attractive on DALYs per dollar, which is what drives the tension in the portfolio results.

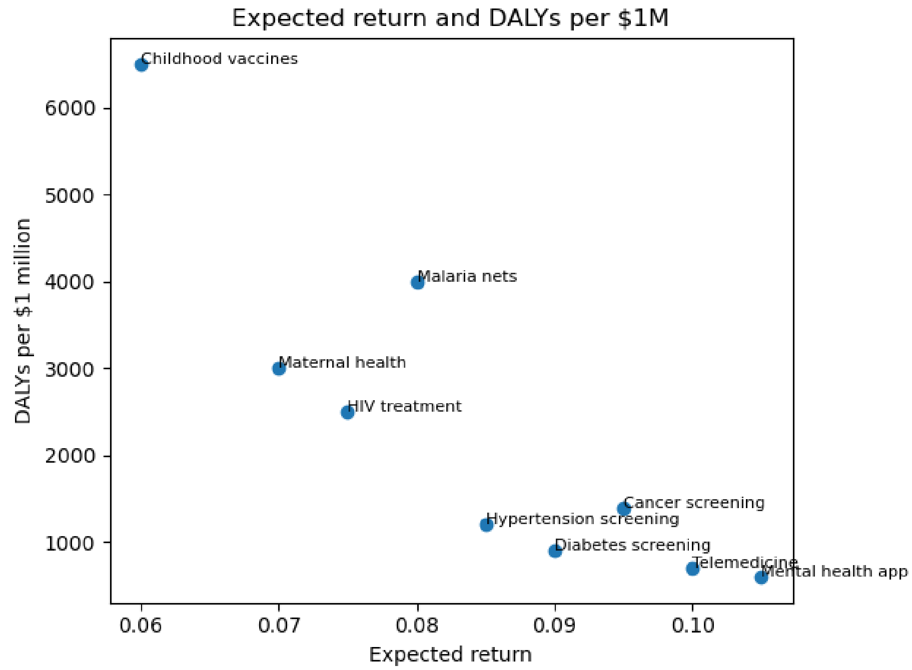

Figure 4.1: Expected return and DALYs per $1 million for the nine simulated health programs.

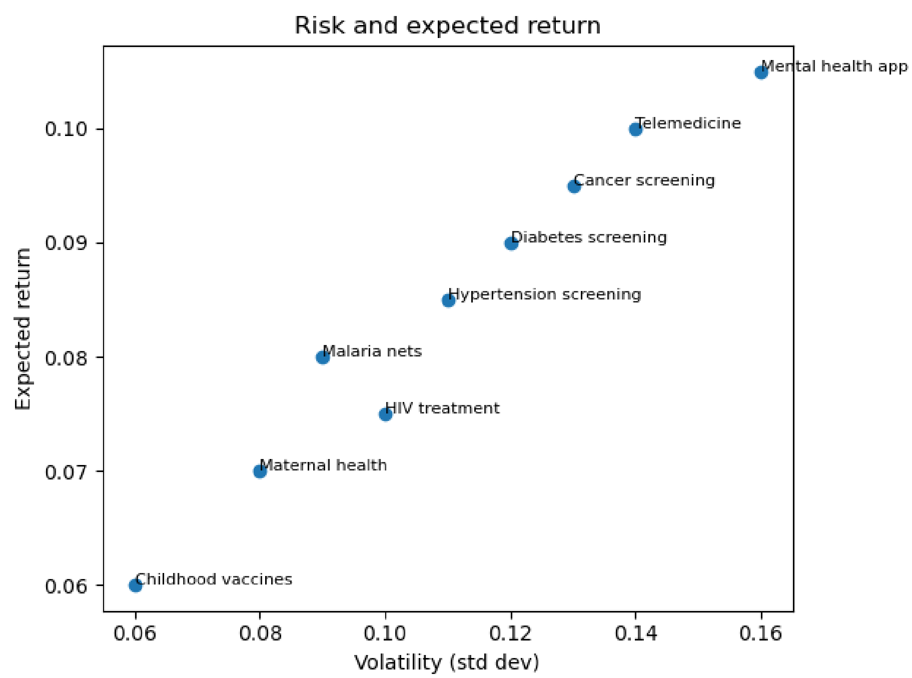

Figure 4.2: Volatility and expected return for the nine simulated health programs.

Chapter 5

Methods

5.1 Sampling portfolio weights

Analytical solutions for the constrained optimization problems with non-negativity restrictions can be complicated. Instead of solving the problems in closed form, I approximate the optimal portfolios by random search over the simplex of long only weights.

A random weight vector w is generated by drawing independent exponential random variables and normalizing:

$$x_i \sim \text{Exponential}(1), \quad w_i = \frac{x_i}{\sum_j x_j}.$$

This guarantees $w_i \geq 0$ and $\sum_i w_i = 1$.

For each portfolio rule, I draw a large number of candidate portfolios (on the order of tens of thousands), compute the objective function and constraints, and keep the portfolio with the highest utility among those that satisfy the constraints.

5.2 Tuning preference parameters

For the simulations in this thesis I fix the risk aversion parameter at $\lambda = 3.0$. For the impact weighted utility I explore a small grid of impact weights β and report results for a value that delivers a clear shift toward high impact programs without collapsing all weight into a single asset.

For the DALY floor portfolios, I choose a grid of floors

$$\bar{I} \in \{1500, 2500, 3500, 4500, 5500\}$$

measured in DALYs per \$1 million, and solve the constrained mean variance problem for each floor where a feasible portfolio exists.

5.3 Computing outcomes

For each candidate portfolio w I compute:

- expected return $E[R_p] = \mu^\top w$,
- variance $\mathrm{Var}(R_p) = w^\top \Sigma w$,
- standard deviation $\sigma_p = \sqrt{\mathrm{Var}(R_p)}$,
- DALYs per \$1 million $I_p = I^\top w$.

These quantities are then used to compare the three portfolio rules and to trace out the impact efficient frontier.

This method is enough for this setup because the universe is small, weights are long only, and the goal is to show the shape of the results, not chase an exact closed form solution.

Chapter 6

Results

6.1 Summary of key portfolios

Table 6.1 reports summary statistics for three representative portfolios:

- the pure mean variance portfolio,
- an impact weighted utility portfolio with $\beta = 0.0002$,
- an impact floor portfolio with $\bar{I} = 4500$ DALYs per $1 million.

Table 6.1: Portfolio level expected return, risk, and DALYs per $1 million for three portfolio rules.

Portfolio	Expected return	Std. dev.	DALYs per $1M
Mean variance	0.093	0.053	1447
Impact utility ($\beta = 0.0002$)	0.068	0.044	5112
Impact floor ($\bar{I} = 4500$)	0.073	0.041	4514

The pure mean variance portfolio delivers the highest expected return among the three but the lowest health impact. The impact weighted portfolio gives up roughly 2.5 percentage points of expected return while increasing DALYs per $1 million by more than a factor of three. The DALY floor portfolio sits between these two, with a higher return than the impact utility portfolio and a DALY level near the imposed floor.

6.2 Portfolio weights

Table 6.2 shows the asset weights for the same three portfolios.

Table 6.2: Weights on each health program for three portfolio rules. Rows sum to one up to rounding.

Portfolio	Vacc.	Mater.	HIV	Mal.	Hyp.	Diab.	Cancer	Tele.	Mental
Mean variance	0.01	0.01	0.03	0.08	0.16	0.16	0.19	0.17	0.19
Impact utility	0.68	0.02	0.05	0.11	0.02	0.01	0.09	0.01	0.00
Impact floor 4500	0.57	0.06	0.01	0.10	0.00	0.03	0.04	0.12	0.07

The mean variance portfolio tilts heavily toward higher return but lower DALY programs such as chronic disease screening, cancer screening, telemedicine, and mental health apps. The impact weighted portfolio shifts most of the capital into childhood vaccines, with smaller allocations to malaria nets, cancer screening, and HIV treatment. The impact floor portfolio also leans toward vaccines and malaria nets but keeps a more diversified exposure to other programs.

6.3 Impact efficient frontier

Figure 6.1 visualizes the tradeoff between expected return and DALYs per $1 million. It plots the three representative portfolios along with the set of DALY floor portfolios.

As the DALY floor is raised from 1500 up toward 5500, expected return falls and the portfolio reallocates toward vaccines and malaria nets. Over a wide range, the investor can increase DALYs per $1 million by several thousand at a cost of only one to two percentage points in expected return.

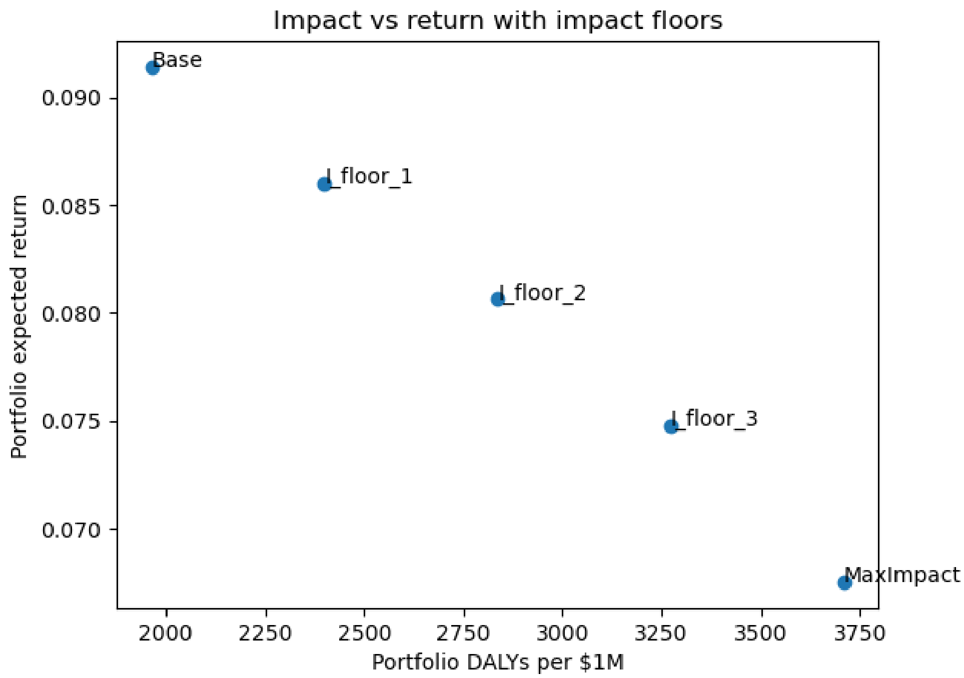

Figure 6.1: Expected return and DALYs per $1 million for the mean variance portfolio, the impact weighted portfolio, and a set of DALY floor portfolios.

Chapter 7

Discussion

The simulations in this thesis highlight several points that are useful for impact investors in global health.

First, treating health impact as a separate objective shifts the efficient set of portfolios in a systematic way. Even a modest impact weight in the utility function can drive large reallocations toward high DALY programs. In the simple universe used here, childhood vaccines and malaria nets dominate most other options in terms of DALYs per dollar, so they absorb most of the weight under impact focused rules.

Second, hard DALY floors are an intuitive way to talk about minimum health outcomes with investors. Instead of asking abstractly how much they value an extra DALY, one can ask what minimum impact level they are willing to accept and then show the implied change in expected return and risk. The impact efficient frontier in Figure 6.1 gives a clean visual summary of these tradeoffs.

Third, the model also makes the limitations clear. The simulation ignores correlations in returns, ignores country level and implementation risk, and treats DALYs per $1 million as exogenous constants. In real settings, DALYs per dollar may fall as the scale of a program expands, and many of the outcomes would be uncertain rather than fixed. Despite these simplifications, the exercise shows that portfolio choice and health cost effectiveness are naturally linked. A portfolio that is optimal on pure financial grounds can be very far from optimal once DALYs are taken into account.

The simple setup makes the result easy to see: once DALYs matter, the efficient set moves toward programs that save a lot of health per dollar, even if their financial return is a bit lower.

7.1 Limitations and Future Work

This model is built to keep the mechanics of health-weighted portfolio choice clear, so several simplifying assumptions are made. First, the DALY estimates used in the simulation are fixed values that do not vary by country, population, or program scale. In real settings, cost-effectiveness depends on local conditions, delivery quality, and changes in disease patterns. Health outcomes are also treated as certain, while real programs involve uncertainty in both impact and implementation.

The financial side is simplified as well. Returns are assumed to be uncorrelated across programs, which removes shared shocks such as economic cycles, supply chain issues, and donor funding risks. Portfolio weights are chosen by random search rather than an exact solver, which keeps the method transparent but only approximates the true optimum. The model also treats health impact as a linear term in utility, even though investors may have threshold preferences, minimum impact requirements, or diminishing returns. The model assumes unlimited scalability and does not incorporate operational constraints or minimum scale requirements for health programs.

These choices point to several natural extensions for future work. A first step would be to replace the stylized DALY inputs with data from the Global Burden of Disease estimates, WHO cost-effectiveness analyses, or studies used by organizations such as GiveWell and ICER. Adding uncertainty to DALY outcomes, financial returns, or both would allow the model to speak more directly to risk in global health programs. Another useful extension is to include correlations between assets and to allow program costs and DALY yields to change with scale. Finally, a dynamic or multi-period version of the model could track how health gains and financial returns evolve over time, especially for programs that require sustained investment.

By expanding in these directions, the framework could move closer to real-world decision making while keeping the core insight: health impact changes the structure of optimal portfolios in clear and measurable ways.

Chapter 8

Conclusion

This thesis builds a small health-weighted portfolio model that incorporates DALYs directly into an investor's objective. Using simulated data for nine stylized global health programs, I compare standard mean variance portfolios, impact weighted utility portfolios, and portfolios that impose minimum DALY floors.

The main result is simple but important. There is no single "impact portfolio". Instead, there is a full impact efficient frontier that trades expected return against DALYs per dollar. In the simulated example, moving along that frontier can increase DALYs per $1 million by several thousand at the cost of only a modest reduction in expected return.

For practice, the model suggests two next steps. The first is to plug in real cost effectiveness estimates from sources such as WHO and UNICEF and to explore how sensitive the frontier is to these inputs. The second is to link this kind of health weighted portfolio choice with actual investment products, for example through blended finance vehicles that use concessional capital to push portfolios toward high DALY programs.

From an academic point of view, the contribution is to show how a standard tool in finance can be extended so that health impact enters as a clear, quantitative term rather than an informal side constraint. From a policy point of view, the hope is that this type of structure can help investors talk more concretely about the tradeoffs they are willing to make between financial return and global health gains.

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Note on Tools Used

During the writing of this thesis, I used ChatGPT to help format and organize the Latex structure and to clean portions of my Python code. Grammarly was used to check grammar and clarity while drafting the text. All ideas, analysis, and final decisions remain my own.