# fin-opt_workflow

October 14, 2025

## 1 FinOpt: Complete Workflow Validation

## 2 Setup

[1]:
```
# --- Path setup: add project root so "src" is importable ---
import os
import sys

PROJECT_ROOT = os.path.abspath(os.path.join(os.getcwd(), ".."))
if PROJECT_ROOT not in sys.path:
    sys.path.insert(0, PROJECT_ROOT)

from datetime import date

import matplotlib.pyplot as plt

# --- Standard libs ---
import numpy as np
import pandas as pd

# --- FinOpt modules (desde /src) ---
from src.income import FixedIncome, IncomeModel, VariableIncome
from src.portfolio import Account, Portfolio
from src.returns import ReturnModel
from src.utils import monthly_to_annual
from src.model import FinancialModel, SimulationResult
```

## 3 Configuration: Seasonality and Contribution

[2]:
```
# --- Seasonality pattern for variable income (12 months, Jan-Dec) ---

# Structure: months = ["Jan", "Feb", "Mar", "Apr", "May", "Jun",
#                       "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]

seasonality_variable = [0.00, 0.00, 0.00, 1.32, 1.32, 1.36,
                        1.24, 1.10, 0.50, 0.90, 1.00, 1.31]
```

```
monthly_contrib_fixed = [0.20, 0.20, 0.20, 0.22, 0.25, 0.25,
                         0.23, 0.23, 0.20, 0.20, 0.20, 0.10]

monthly_contrib_variable = [1.0] * 12
```

## 4 Initialize FinancialModel

[3]:
```
# IncomeModel Instantiation
income = IncomeModel(
    fixed=FixedIncome(
        base=1_480_000.0,        # CLP/month
        annual_growth=0.03,      # 3% nominal annual growth
        salary_raises={
            date(2026, 4, 1): 400_000,  # +400k in April 2026
            date(2027, 4, 1): 400_000   # +400k in April 2027
        },
        name="fixed"
    ),
    variable=VariableIncome(
        base=150_000.0,          # Base variable income
        seasonality=seasonality_variable,
        sigma=0.10,              # 10% monthly noise
        floor=0.0,               # No negative income
        cap=400_000.0,           # Maximum 400k/month
        annual_growth=0.0,       # No growth in variable
        name="variable"
    ),
)

# --- Define contribution strategy ---
income.monthly_contribution = {
    "fixed": monthly_contrib_fixed,  # Custom monthly fractions
    "variable": monthly_contrib_variable,          # 100% of variable income
}

# --- Account configuration: Conservative vs Aggressive ---
accounts = [
    Account.from_annual(
        name="Emergency",
        annual_return=0.04,         # 4% annual (conservative)
        annual_volatility=0.03,     # 2% volatility
        initial_wealth=0
    ),
    Account.from_annual(
        name="Growth",
        annual_return=0.12,         # 14% annual (aggressive)
        annual_volatility=0.14,     # 15% volatility
        initial_wealth=0
    )
]

# --- Correlation matrix (2x2) ---
# Emergency and Growth have moderate positive correlation (  = 0.3)
correlation_matrix = np.array([
    [1.0, 0.2],
    [0.2, 1.0]
])

# --- Initialize FinancialModel ---
model = FinancialModel(income, accounts, default_correlation =␣
  ↪correlation_matrix)
model
```

[3]:
```
FinancialModel(M=2, accounts=['Emergency', 'Growth'], cache=enabled)
```

## 5 Simulation parameters

[4]:
```
# --- Simulation parameters ---
n_sims = 500
months = 48
start_date = date(2025, 10, 1)
```

## 6 Income Module

Total monthly income at time $t$ is composed of fixed and variable parts:

$$Y_t = y_t^{\text{fixed}} + Y_t^{\text{variable}}$$

---

### 6.1 Fixed Income

The fixed component, $y_t^{\text{fixed}}$, reflects a baseline salary subject to compounded annual growth $g$ and scheduled raises $d_k, \Delta_k$ (e.g., promotions or tenure milestones):

$$y_t^{\text{fixed}} = \text{current\_salary}(t) \cdot (1+m)^{\Delta t}$$

where $m = (1+g)^{1/12} - 1$ is the **monthly compounded rate**, and $\Delta t$ represents time since the last raise.

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## 6.2 Variable Income

The variable component, $Y_t^{\text{variable}}$, models irregular income sources (e.g., freelance work or bonuses) with:

- **Seasonality**: $s \in \mathbb{R}^{12}$ (multiplicative monthly factors),
- **Noise**: $\epsilon_t \sim \mathcal{N}(0, \sigma^2)$ (Gaussian shocks),
- **Growth**: same compounded rate $m$ applied to a base income level,
- **Boundaries**: optional floor and cap constraints.

The underlying stochastic projection is:

$$\tilde{Y}_t = \max(\text{floor},\ \mu_t(1+\epsilon_t)), \quad \text{where } \mu_t = \text{base} \cdot (1+m)^t \cdot s * (t \bmod 12)$$

Then, guardrails are applied as:

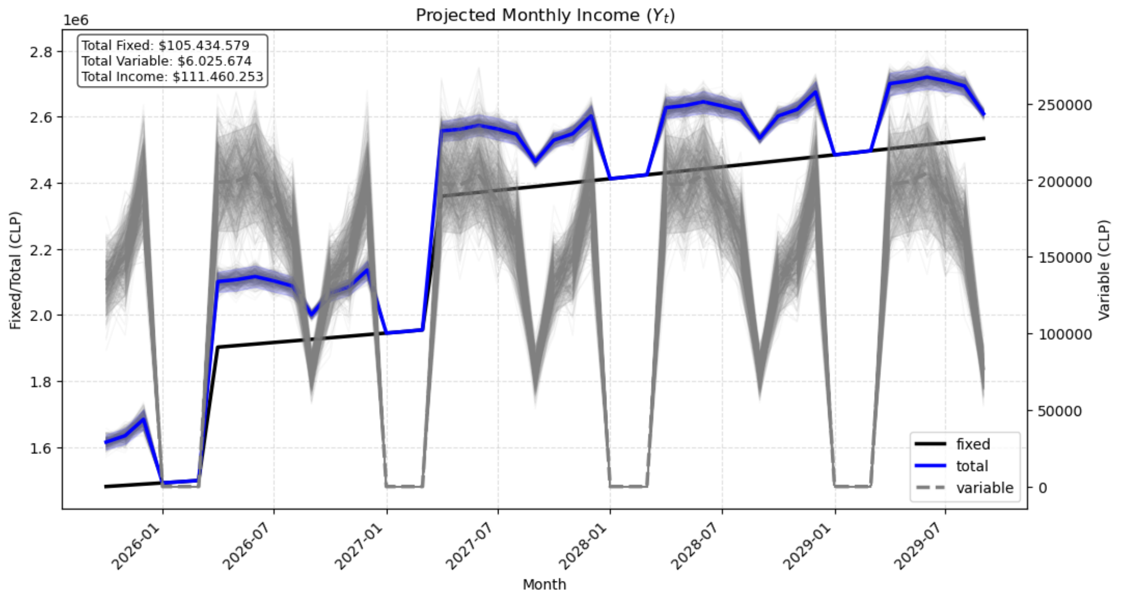
$$Y_t^{\text{variable}} = \begin{cases} 0 & \text{if } \tilde{Y}_t < 0 \\ \tilde{Y}_t & \text{if } 0 \le \tilde{Y}_t \le \text{cap} \\ \text{cap} & \text{if } \tilde{Y}_t > \text{cap} \end{cases}$$

**Note:** In expectation (ignoring noise truncation), $\mathbb{E}[Y_t] = y_t^{\text{fixed}} + \mu_t$

## 6.3 Income Projection

Dual-axis plot with: - **Left axis**: Fixed income (deterministic) + Total income - **Right axis**: Variable income (stochastic with trajectories) - **Trajectories**: Individual noise realizations (n=300) - **Confidence band**: 95% CI for variable income

```
[5]: # Income Projection Simulation
model.plot(mode='income', T=months, start=start_date)
```



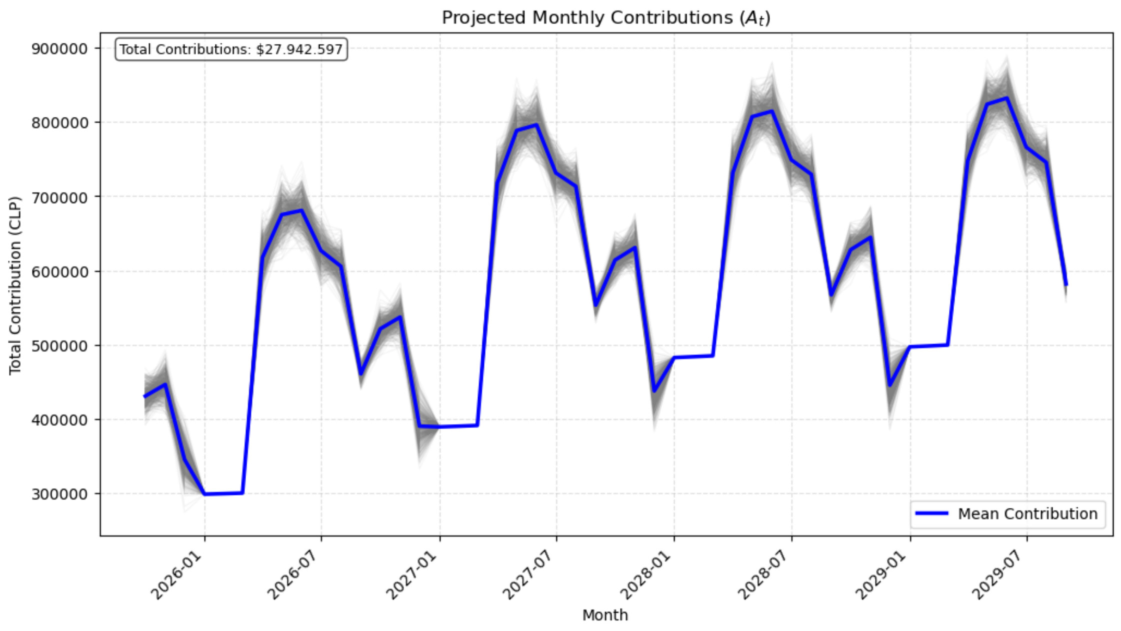
### 6.4 Contribution Projection

A fraction of income is allocated each month through calendar-rotating schedules:

$$A_t = \alpha^f_{(t+\text{offset}) \bmod 12} \cdot y_t^{\text{fixed}} + \alpha^v_{(t+\text{offset}) \bmod 12} \cdot Y_t^{\text{variable}}$$

where $\alpha^f, \alpha^v \in [0,1]^{12}$ control the fixed and variable contribution rates by applying the 12-month fractional arrays to projected incomes, rotated according to `start` date and repeated cyclically for horizons $> 12$ months.

```
[6]: # Contribution Projection Simulation
     model.plot(mode='contributions', T=months, start=start_date)
```



## 7 Return Module

### 7.1 Multi-Account Return Model

For $M$ accounts with correlated returns:

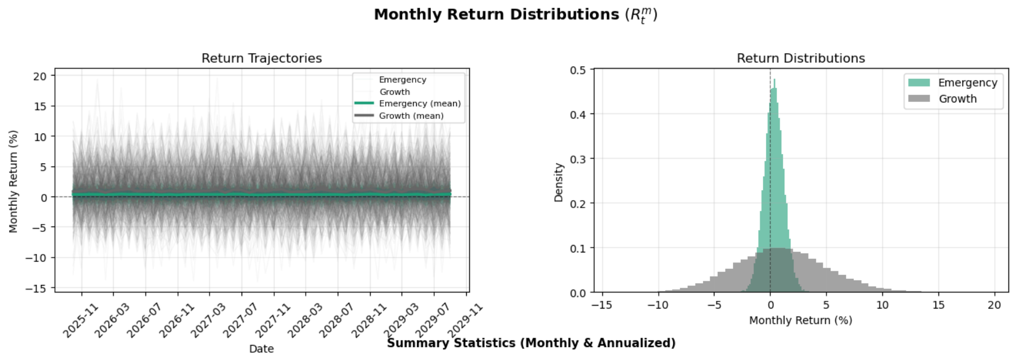
$$1 + R_t^m \sim \text{LogNormal}(\mu^m_{\log}, \Sigma)$$

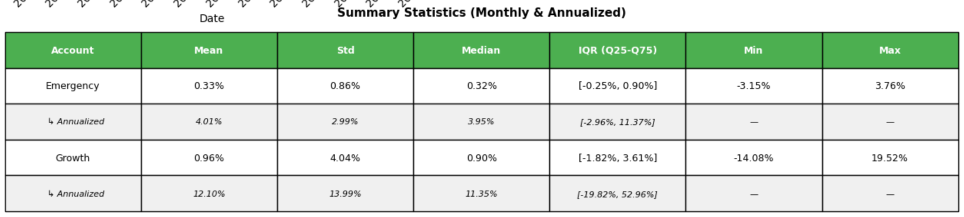
where $\Sigma = D \cdot \rho \cdot D$ is the covariance matrix: - $D = \text{diag}(\sigma^1_{\log}, \dots, \sigma^M_{\log})$ - $\rho \in \mathbb{R}^{M\times M}$ is the correlation matrix (symmetric, PSD)

## 7.2 Monthly Return Distribution (Marginal Analysis)

Visualizes IID monthly returns across both accounts with 4 panels: - **Trajectories**: Individual paths for each account - **Histograms**: Marginal distributions (overlaid) - **Statistics**: Mean, std, quantiles per account

```
[7]: model.plot(mode = 'returns', T = months, start=start_date)
```





**Summary Statistics (Monthly & Annualized)**

| Account | Mean | Std | Median | IQR (Q25-Q75) | Min | Max |
|---|---|---|---|---|---|---|
| Emergency | 0.33% | 0.86% | 0.32% | [-0.25%, 0.90%] | -3.15% | 3.76% |
| ↳ *Annualized* | *4.01%* | *2.99%* | *3.95%* | *[-2.96%, 11.37%]* | — | — |
| Growth | 0.96% | 4.04% | 0.90% | [-1.82%, 3.61%] | -14.08% | 19.52% |
| ↳ *Annualized* | *12.10%* | *13.99%* | *11.35%* | *[-19.82%, 52.96%]* | — | — |

T=48 months | n_sims=500 | seed=None

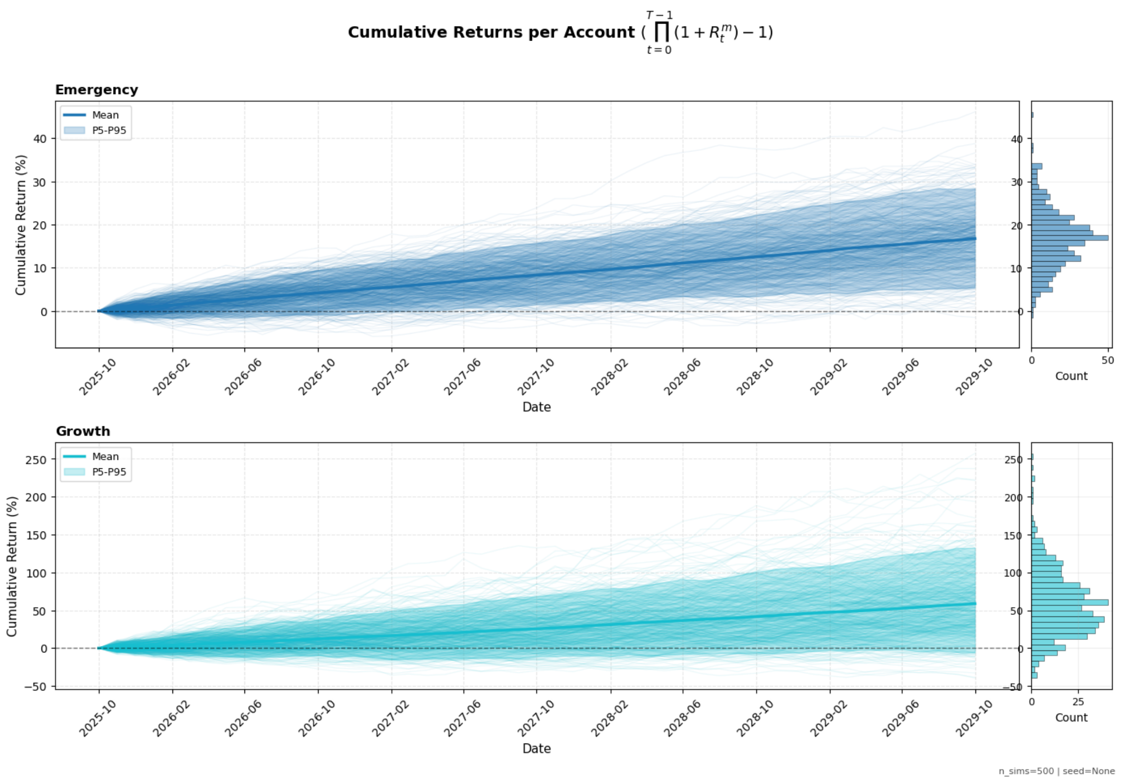
## 7.3 Cumulative Returns per Account

For $M$ accounts with correlated returns:

$$R^m_{\text{cm}}(T) = \prod_{t=0}^{T-1}(1 + R^m_t) - 1$$

**Cross-sectional correlation** persists through time but does not compound.

```
[8]: model.plot(mode = 'returns_cumulative', T = months, start=start_date)
```



## 7.4 Horizon Analysis: Time Diversification by Account

```
[9]: # --- Horizon analysis (average portfolio behavior) ---
mode = 'returns_horizon'
model.plot(mode = 'returns_horizon')
```

```
================================================================================
=====
HORIZON ANALYSIS - Emergency
================================================================================
=====
 Horizon |   Expected |  Volatility |  P(Loss) |     P25-P75 |    SNR
 (years) |     Return |        (±1 ) |          |       Range |
--------------------------------------------------------------------------------
-----
    1.0  |       4.0% |        3.0% |     9.1% |        4.0% |  1.33
    2.0  |       8.2% |        4.2% |     2.7% |        5.7% |  1.92
    3.0  |      12.5% |        5.2% |     0.8% |        7.0% |  2.40
    5.0  |      21.7% |        6.7% |     0.1% |        9.0% |  3.23
   10.0  |      48.0% |        9.5% |     0.0% |       12.8% |  5.06
   15.0  |      80.1% |       11.6% |     0.0% |       15.7% |  6.89
   20.0  |     119.1% |       13.4% |     0.0% |       18.1% |  8.88
```

```
================================================================================
=====

================================================================================
=====
HORIZON ANALYSIS - Growth
================================================================================
=====
 Horizon |  Expected | Volatility |  P(Loss) |     P25-P75 |    SNR
 (years) |    Return |       (±1 ) |          |      Range |
--------------------------------------------------------------------------------
-----
    1.0   |     12.0% |      14.0% |    19.6% |      18.9% |  0.86
    2.0   |     25.4% |      19.8% |     9.9% |      26.7% |  1.28
    3.0   |     40.5% |      24.2% |     4.7% |      32.7% |  1.67
    5.0   |     76.2% |      31.3% |     0.7% |      42.2% |  2.44
   10.0   |    210.6% |      44.3% |     0.0% |      59.7% |  4.76
   15.0   |    447.4% |      54.2% |     0.0% |      73.1% |  8.25
   20.0   |    864.6% |      62.6% |     0.0% |      84.5% | 13.81
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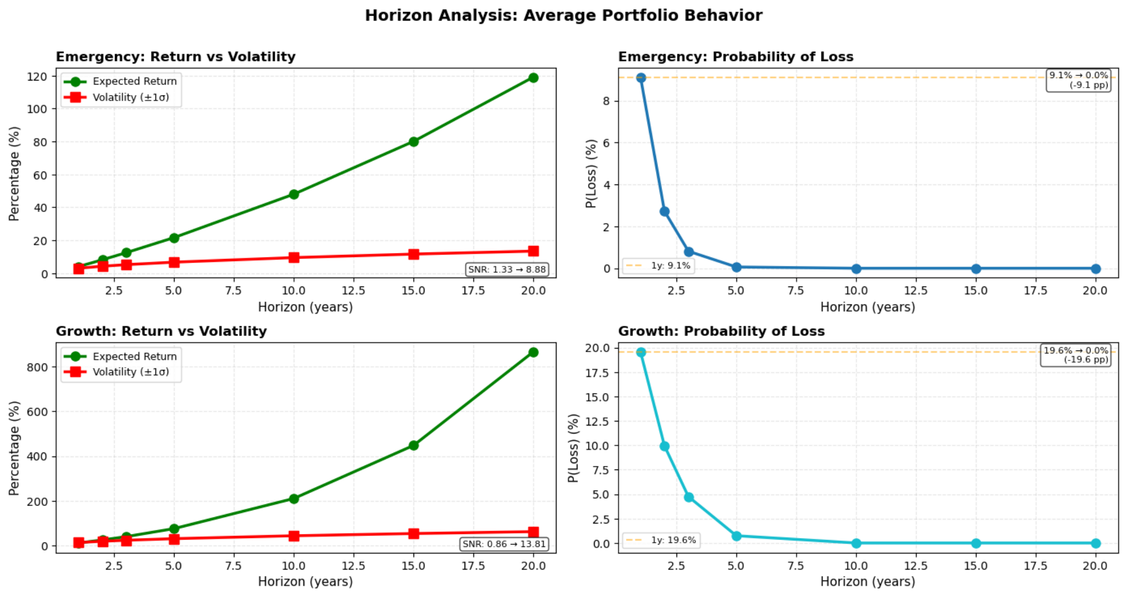
```



## 8 Portfolio Module

### 8.1 Wealth Projection Under Allocation Policy

**Recursive dynamics**: Wealth evolves as:

$$W_{t+1}^m = (W_t^m + A_t^m)\,(1 + R_t^m)$$

where $A_t^m = x_t^m \cdot A_t$ is the contribution allocated to account $m$ via policy $X = \{x_t^m\}_{t,m}$.

**Closed-form representation**:

$$W_t^m = W_0^m\, F_{0,t}^m + \sum_{s=0}^{t-1} A_s\, x_s^m\, F_{s,t}^m$$

with accumulation factor $F_{s,t}^m = \prod_{r=s}^{t-1}(1 + R_r^m)$.

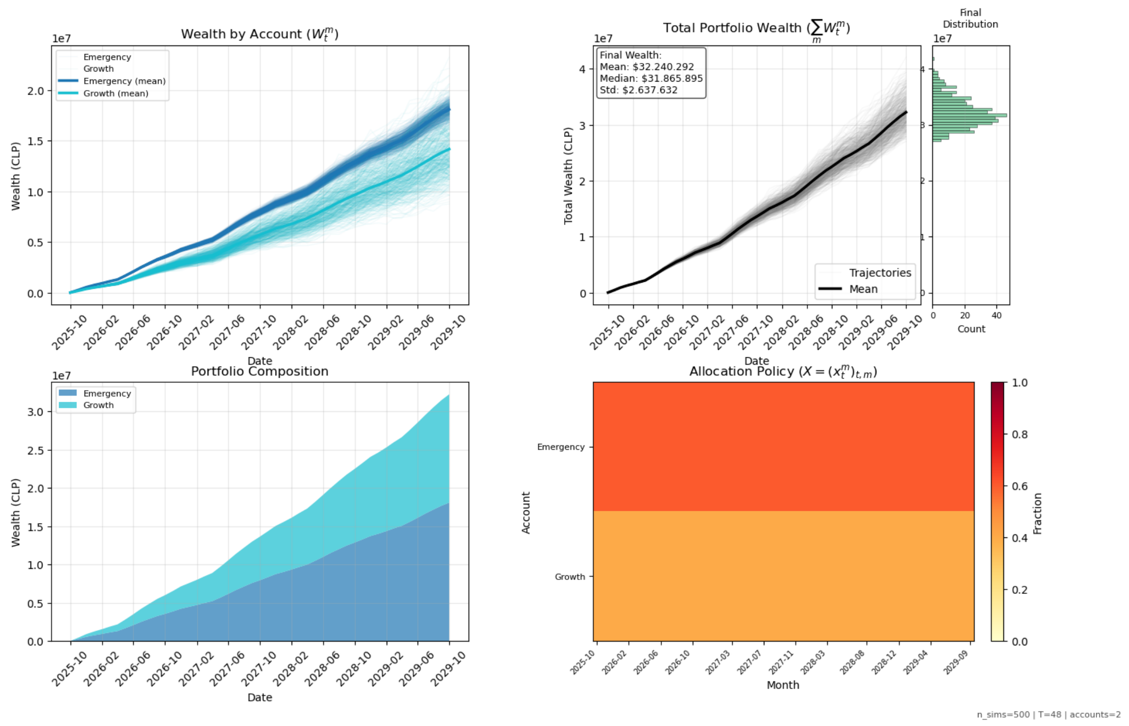
**Key insight**: $W_t^m(X)$ is **linear affine in policy** $X$ $\rightarrow$ analytical gradients enable convex optimization.

**What to observe**: - Top-left: wealth per account with Monte Carlo trajectories - Top-right: total wealth + final distribution histogram - Bottom-left: portfolio composition over time - Bottom-right: allocation policy heatmap

[10]:
```
# Define Allocation Policy

# --- Static allocation: 60% Emergency, 40% Growth ---
X_static = np.tile([0.6, 0.4], (months, 1))  # shape (months, 2)

# Project monthly Wealth
model.plot(mode = 'wealth', start=start_date, T=months, X=X_static)
```



```
[ ]:
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