GOAL-BASED WEALTH MANAGEMENT, ROBO-ADVISING

Changes in the Investment Landscape

- 1. From targeting portfolio value (wealth) to targeting income streams (Dimensional Fund Advisors, Merton).
- 2. From asset-driven portfolio management to liability-driven investing.
- 3. No more "policy" portfolios, but goal based investing for individuals, factor-based investing for institutions (smart beta).
- 4. From Defined Benefit (DB) to Defined Contribution (DC). Individuals need to make their own decisions, despite known research pointing to their inability to do so.
- 5. Two pieces of the portfolio: (i) liability hedging (including healthcare), and (ii) aspiration seeking.
- 6. From investment products to investment solutions.

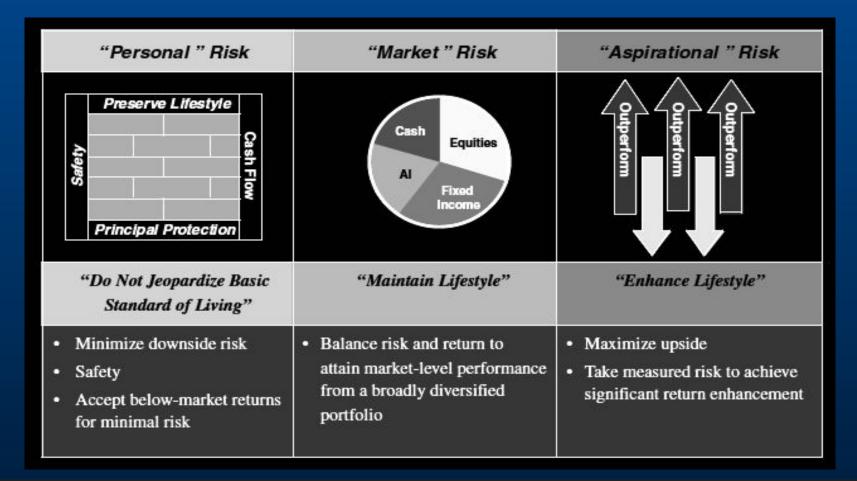
The five Hs:

- 1. Holdings
- 2. House
- 3. Health
- 4. Human Capital
- 5. Happiness

Challenges

- Low interest rates: challenging pension liability present values.
- Low equity premium: poor growth and portfolio return.
- Longevity risk.

Risks (Chhabra, JPM 2005)



Markowitz Mean-Variance Optimization

Minimize: Risk = Portfolio return variance subject to: a given level of return

or

Maximize: (Mean return) - (Risk Aversion) \times (Variance of return)

$$\max_{\mathbf{w}} \mathbf{w}^{\top} \mu - \frac{\gamma}{2} \mathbf{w}^{\top} \mathbf{\Sigma} \mathbf{w}$$

subject to

$$\mathbf{w}^{\top} \mathbf{1} = 1, \qquad \mathbf{1} = [1, 1, 1, ..., 1]^{\top} \in \mathcal{R}^{n}$$

The solution is:

$$\mathbf{w} = rac{1}{\gamma} \mathbf{\Sigma}^{-1} \left[\mu - \left(rac{\mathbf{1}^{ op} \mathbf{\Sigma}^{-1} \mu - \gamma}{\mathbf{1}^{ op} \mathbf{\Sigma}^{-1} \mathbf{1}}
ight) \mathbf{1}
ight] \in \mathcal{R}^n$$

Solution Math

To solve this maximization problem, we set up the Lagrangian with coefficient λ :

(A-1)
$$\max_{w,\lambda} L = w' \mu - \frac{\gamma}{2} w' \Sigma w + \lambda [1 - w' 1].$$

The first-order conditions are

(A-2)
$$\frac{\partial L}{\partial w} = \mu - \gamma \Sigma w - \lambda \mathbf{1} = 0,$$
(A-3)
$$\frac{\partial L}{\partial \lambda} = 1 - w' \mathbf{1} = 0.$$

$$\frac{\partial L}{\partial \lambda} = 1 - w' \mathbf{1} = 0$$

Note that equation (A-2) is a system of n equations. Rearranging equation (A-2) gives

(A-4)
$$\Sigma w = \frac{1}{2}[\mu - \lambda 1],$$

and premultiplying both sides of this equation by Σ^{-1} gives

(A-5)
$$w = \frac{1}{\gamma} \Sigma^{-1} [\mu - \lambda 1].$$

Final solution

The solution here for portfolio weights is not yet complete, as the equation contains λ , which we still need to solve for. Premultiplying equation (A-5) by 1' gives

(A-6)
$$1'w = \frac{1}{\gamma} 1' \Sigma^{-1} [\mu - \lambda 1],$$

(A-7)
$$1 = \frac{1}{\gamma} [\mathbf{1}' \Sigma^{-1} \mu - \lambda \mathbf{1}' \Sigma^{-1} \mathbf{1}],$$

which can now be solved for λ to get

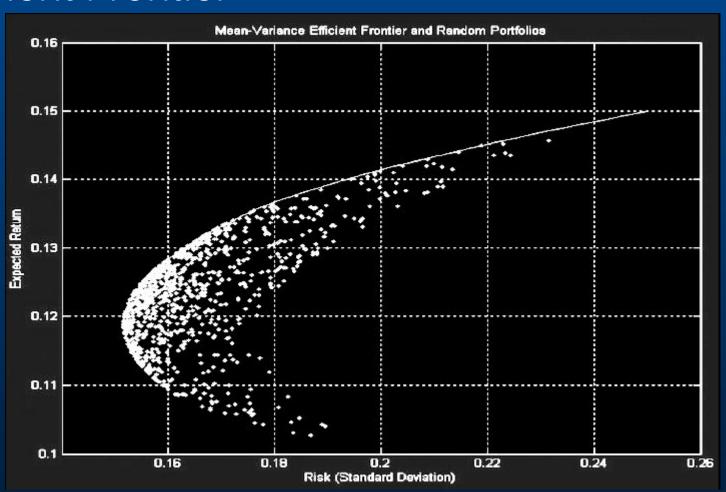
(A-8)
$$\lambda = \frac{1'\Sigma^{-1}\mu - \gamma}{1'\Sigma^{-1}1}.$$

Plugging λ back into equation (A-5) gives the closed-form solution for the optimal portfolio weights:

$$w = \frac{1}{\gamma} \Sigma^{-1} \left[\mu - \left(\frac{\mathbf{1}' \Sigma^{-1} \mu - \gamma}{\mathbf{1}' \Sigma^{-1} \mathbf{1}} \right) \mathbf{1} \right] \in \mathbb{R}^n.$$

This optimal solution w is an n-vector and is easily implemented, given that it is analytical.

Efficient Frontier



Persona-Based Mental Accounts

- 1. Investors consider their portfolios not as a whole but as a pyramid of sub-portfolios, arranged by goals.
- 2. Investors want the highest probability of reaching their goals (retirement, education, bequest).
- 3. Nonlinear structured products may be better at tuning a portfolio that is goal-based.

Behavioral Portfolio Optimization

JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 45, No. 2, Apr. 2010, pp. 311–334 COPYRIGHT 2010, MICHAEL G. FOSTER SCHOOL OF BUSINESS, UNIVERSITY OF WASHINGTON, SEATTLE, WA 98195 doi:10.1017/S0022109010000141

Portfolio Optimization with Mental Accounts

Sanjiv Das, Harry Markowitz, Jonathan Scheid, and Meir Statman*

Abstract

We integrate appealing features of Markowitz's mean-variance portfolio theory (MVT) and Shefrin and Statman's behavioral portfolio theory (BPT) into a new mental accounting (MA) framework. Features of the MA framework include an MA structure of portfolios, a definition of risk as the probability of failing to reach the threshold level in each mental account, and attitudes toward risk that vary by account. We demonstrate a mathematical equivalence between MVT, MA, and risk management using value at risk (VaR). The aggregate allocation across MA subportfolios is mean-variance efficient with short selling. Short-selling constraints on mental accounts impose very minor reductions in certainty equivalents, only if binding for the aggregate portfolio, offsetting utility losses from errors in specifying risk-aversion coefficients in MVT applications. These generalizations of MVT and BPT via a unified MA framework result in a fruitful connection between investor consumption goals and portfolio production.

Maximize mean wealth at horizon

Subject to:

Probability of shortfall less than H should be less than alpha

Optimizing Portfolios with Mental Accounts

See the paper by Das, Markowitz, Scheid, and Statman (2010) in the *Journal of Financial and Quantitative Analysis*.

$$\max_{\mathbf{w}} \mathbf{w}^{\mathsf{T}} \mu, \quad s.t. \quad \mathsf{Prob}[r \leq H] \leq \alpha$$

For normal returns r, the constraint may be stated explicitly as

$$H \leq \mathbf{w}^{\mathsf{T}} \mu + \Phi^{-1}(\alpha) [\mathbf{w}^{\mathsf{T}} \mathbf{\Sigma} \mathbf{w}]^{1/2}$$

Iterative Solution to extract risk aversion

$$H = w(\gamma)'\mu + \Phi^{-1}(\alpha)[w(\gamma)'\Sigma w(\gamma)]^{1/2},$$
 $w(\gamma) = \frac{1}{\gamma}\Sigma^{-1}\left[\mu - \left(\frac{\mathbf{1}'\Sigma^{-1}\mu - \gamma}{\mathbf{1}'\Sigma^{-1}\mathbf{1}}\right)\mathbf{1}\right].$

Example of BPT/MA

Let's use an example of a portfolio of three securities.

Security	Expected Returns	Standard Deviations
Bond	5%	5%
Low-risk stock	10%	20%
High-risk stock	25%	50%

The correlation between the two stocks is 0.20, and all other correlations are zero.

Assume the investor has separate goals and sub-portfolios:

Goal (subportfolio)	Current allocation	Time Horizon	Annualized Return goal	Total Accumulation goal
Bequest	\$200,000	25 years	26.35%	\$69,248,625
Education	\$200,000	3 years	12.18%	\$282,343
Retirement Account	\$600,000	15 years	10.23%	\$2,586,118

Sub-portfolios and overall portfolio

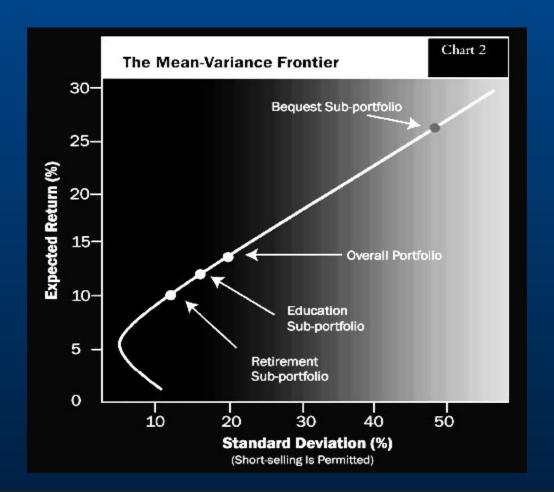
The Three Goal Sub-portfolios and the Overall Portfolio

Assets	Retirement Sub-portfolio	Education Sub-portfolio	Bequest Sub-portfolio	Overall Portfolio
Bond	53.94%	37.87%	(78.90%)	24.16%
Low Risk Stock	26.56%	34.99%	96.20%	42.17%
High Risk Stock	19.50%	27.14%	82.70%	33.67%
Total Weights	100%	100%	100%	100%
Expected Return	10.23%	12.18%	26.35%	13.84%
Std. Deviation	12.30%	16.57%	49.13%	20.32%

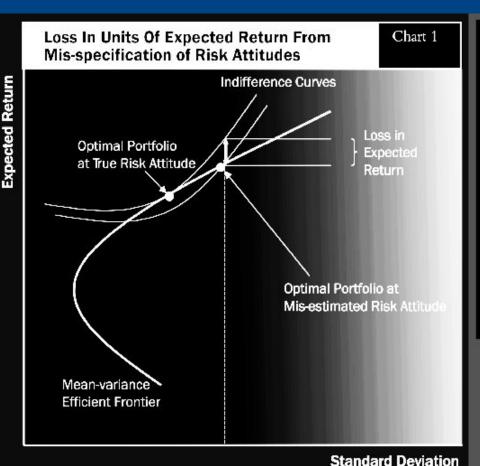
The expected return of the overall portfolio is the weighted average of the expected returns of the sub-portfolios.

The risk of the overall portfolio is **not** the weighted average of the risk of the sub-portfolios.

Mean-Variance Frontier



Loss from mis-estimation of risk attitude



	Mis-specification of						
	risk a	coefficient					
Risk aversion (γ)	10%	20%	30%				
3.7950	2.50	10.94	28.72				
2.7063	3.50	15.34	40.27				
0.8773	5.29	23.15	44.22				
	(Numbers in basis poin						

Mistakes in ascertaining risk preferences can cost the investor dearly.

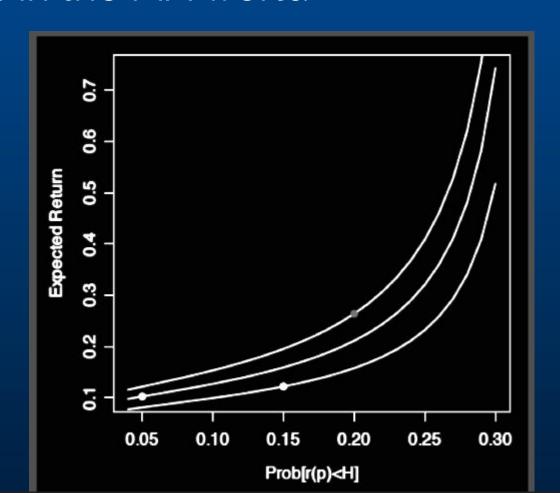
Risk as a probability of loss

Sub-portfolio Risk Defined by the Probability of Losses Education Retirement Bequest Sub-portfolio Sub-portfolio Sub-portfolio 10.23% 12.18% 26.35% Expected Return Std. Deviation 12.30% 16.57% 49.13% No more than a 15% No more than a 20% No more than a 5% Probability-Based probability of losing probability of losing probability of losing Risk Language more than 10% more than 5% more than 15% Mean-variance problem: Minimize Risk (variance) subject to minimum level of Expected Return. Behavioral portfolio theory: Maximize Return subject to a maximum probability of falling below a threshold.

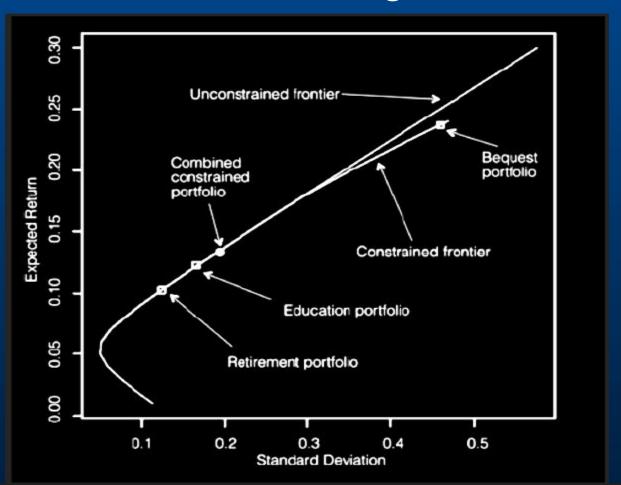
Probability of shortfall

- D. 1	0.000	0.000	0.0==0	00 00 00
Risk aversion:	$\gamma=3.7950$	$\gamma=2.7063$	$\gamma=0.8773$	60:20:20 mix
	Retirement	Education	Bequest	Aggregate
	Sub-portfolio	Sub-portfolio	Sub-portfolio	Portfolio
Threshold (H)	Prob[r < H]	Prob[r < H]	Prob[r < H]	Prob[r < H]
-25.00%	0.00	0.01	0.15	0.03
-20.00%	0.01	0.03	0.17	0.05
-15.00%	0.02	0.05	0.20	0.08
-10.00%	0.05	0.09	0.23	0.12
-5.00%	0.11	0.15	0.26	0.18
0.00%	0.20	0.23	0.30	0.25
5.00%	0.34	0.33	0.33	0.33
10.00%	0.49	0.45	0.37	0.42
15.00%	0.65	0.57	0.41	0.52
20.00%	0.79	0.68	0.45	0.62
25.00%	0.89	0.78	0.49	0.71
Mean return	10.23%	12.18%	26.35%	13.84%
Std. deviation	12.30%	16.57%	49.13%	20.32%

Frontiers in the MA world



MV frontier with short-selling



Python Program Code

Markowitz_MeanVariance_Optimization_BPT.ipynb

Based on Behavioral Finance

- The 2017 Nobel Prize was awarded to Richard Thaler and the ideas in goals-based wealth management emanate from this literature.
- Markowitz Portfolio Theory (1952).
- Prospect Theory (Kahneman and Tversky 1979).
- Behavioral Portfolio Theory (Shefrin and Statman, 2000).
- Disposition Effect (Shefrin and Statman, 1985).
- Mental Accounting Theory (Thaler 1985; 1989).
- MVT and BPT are mapped to each other (Das, Markowitz, Scheid, Statman, 2012).

GBWM - Operationalization

- A clear articulation of investor goals;
- A statement of the probability of achieving the goal that is expected by the investor;
- A loss threshold with a chosen small probability with which the investor is willing to allow a breach of this threshold; and
- A set of preferences for actions to be taken if and when achieving the investor's goals with the attached probabilities becomes infeasible.

Traditional financial planning is not GBWM

GBWM *includes* optimizing risk-return tradeoffs and assessing return relative to a benchmark, but is *much more*.

- 1. Also assesses performance relative to goals.
- 2. Allows multiple goals versus a limited single portfolio focus.
- Treats upside potential and downside risk separately, and does not bundle everything into a single standard deviation number.
- 4. Emphasizes long-run performance and not just immediate performance against a benchmark.
- 5. Assesses investor preferences more accurately.
- 6. Seamlessly brings the discussion of remedial actions to the origination and planning phase.

GBWM - Main Tenets

- Measure performance relative to goals rather than relative to benchmarks.
- Nevins (2004): recognize investor's preferences and biases.
- Recognize behavior: loss aversion, mental accounting, (advocated by Zwecher 2010).
- Ameliorate biases: overconfidence, hindsight bias, overreaction, belief perseverance, and regret avoidance.
- Brunel (2015): trade-off greed vs fear, dreams vs nightmares.

The Mathematical Underpinnings

We first ask the investor to specify 8 pieces of information:

- 1) Their time frame (Investment Tenure)
- 2) Their initial investment (Initial Wealth)
- 3) Their goal wealth (Target Wealth)
- 4) The probability they would like to maintain of reaching their goal wealth (Target Probability)
- 5) The wealth they would not want to end up being below (Loss Threshold)
- 6) The probability they would like to maintain of ending above the Loss Threshold (Loss Threshold Probability)
- 7) Selecting one of three options for their investment preferences in good times.
- 8) Selecting one of three options for their investment preferences in bad times.

The Goals and the Loss Threshold each define parabolas in the risk-return plane.

$$\mu = \frac{1}{2}\sigma^2 + \frac{z_0}{\sqrt{t}}\sigma + \frac{1}{t}\ln\left(\frac{W(t)}{W(0)}\right).$$

Base Case for Goals:

- 1) Investment Tenure: 10 years.
- 2) Initial Wealth: \$400,000
- 3) Target Wealth: \$500,000
- 4) Target Probability: 80%

Figure 2: The Dependence of Goal Probability Level Curves on Probability Levels

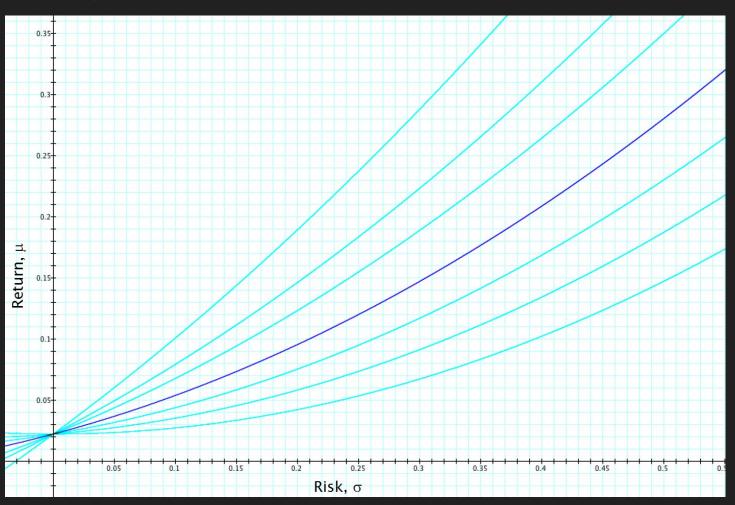
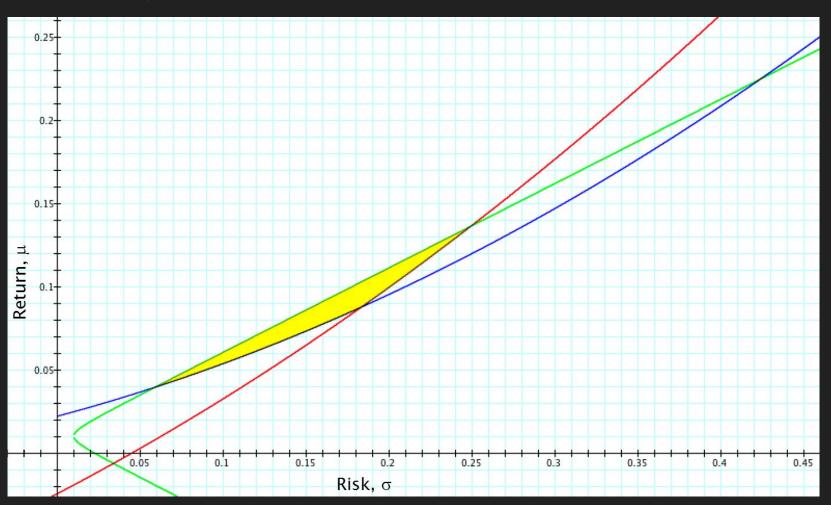


Figure 4: Feasible Portfolios that Satisfy the Investor's Goals and Loss Threshold



Metrics - Upside

Assume that we have created a portfolio using the model structure described in the previous section. For example, suppose we wanted the portfolio return (r) to be at least H% return per year with probability p, and to not lose more than L% a year with q probability. Our portfolio construction results in $P = \int_{-\infty}^{\infty} f(r) \, dr \ge p$, and

$$Q = \int_{-\infty}^{L} f(r) dr \le q$$
, where $f(r)$ is the density function for portfolio returns.

We define the following three metrics.

Upside, defined as

$$\frac{U}{P}$$

where

$$U = \int_{H}^{\infty} (r - H) f(r) dr$$

Barring a discounting term, this expression describes the value of a call option on the rate of return with strike rate *H*. We usually denote such options on rates as caps. Next we define

Metrics - Downside & Performance

Downside, defined as

 $\frac{D}{Q}$

where

$$D = \int_{-\infty}^{L} (L - r) f(r) dr$$

This is akin to a put option on the rate of return, i.e., a floor. This is a measure of downside risk and is the return-based analog to the widely used dollar risk measure of expected shortfall. Finally we present

Omega, i.e.,

$$\Omega = \frac{U}{D}$$

Intuitively, Ω tells us how many units of excess return over the goal was earned for every unit of expected shortfall below the loss threshold. It is an interesting goal versus risk trade-off for GBWM.

Using Bots

Awards

Text synthesis, Picture, Commercial

engagement.

Text synthesis, Avatar, Commercial

by Marketeer.co since Nov 2017 in English, Web, Facebook, Branded

conversations, Campaign, Customer service, Sales, Text recognition,

questions related to Marketeerco. It uses artificial

in Share

by AIChatbots.sq since Oct 2017 in English, Facebook, Text recognition.

Anderson is a chatbot that provides information about

Marketeer is a hybrid chat bot, it can answer all of your

intelligence an machine learning to optimize the customer

So, a customer service platform that learns from our agents

and respond to our clients while improving our customer





TOPBOTS

THE BEST OF BRAND BOTS

BUSINESS & FINANCE ENTERTAINMENT FOOD HEALTH & FITNESS LIFESTYLE NEWS & MEDIA SHOPPING SOCIAL GOOD SPORTS TRAVEL



nternational Media Enquir

Email Erwin Phone (GMT +1):

Erwin van Lun CEO/Founder Chatbots.

+316 21 567 657



1. Chat with Chatbot

2. Chat Messenger

Hot on AI Zone

AI forum hosted by Chatbots.o Are there a complete opensource chat bot to use?

- > Javascript tag and put in set t The most sensational A.I. nev
- > Crash with large top file > Python 3.x Implementation of AIML 2.0







NIKE Shopping



SUBWAY Food



MACALLAN Food









Using Derivatives to sharpen goal-targeting

Options and Structured Products in Behavioral Portfolios, (with Meir Statman), 2013, Journal of Economic Dynamics and Control, 37(1), 137-153. http://algo.scu.edu/~sanjivdas/JEDC_FINAL_PROOF.pdf
Puts are needed when the threshold return is high

			Pa	mel C: H =	$-5\%, \alpha = 0.0$	5			
	LowRisk	MedRisk	HighRisk	LongPut			Portfolio R	eturn Mome	nts
Strike	w_1	w_2	w_3	w ₄	Pr[r < H]	Mean	Std Dev	Skewness	Kurtosis
No put	0.6964	0.2008	0.1028	0.0000	0.0498	0.0806	0.0793	0.0000	0.0000
0.8	0.6986	0.1998	0.1016	0.0000	0.0491	0.0803	0.0788	0.0008	-0.0010
0.9	0.6982	0.2002	0.1016	0.0000	0.0491	0.0803	0.0788	0.0003	-0.0002
1	0.6971	0.2000	0.1028	0.0001	0.0495	0.0805	0.0792	0.0011	-0.0005
1.1	0.6962	0.2000	0.1035	0.0003	0.0496	0.0806	0.0793	0.0032	0.0000
1.2	0.6977	0.1994	0.1029	0.0000	0.0495	0.0805	0.0792	0.0000	0.0000

			1.5	anel D : $H =$	$=$ 0%, $\alpha =$ 0.00	•			
	LowRisk	MedRisk	HighRisk	LongPut			Portfolio R	eturn Mome	nts
Strike	w_1	w ₂	w_3	w_4	Pr[r < H]	Mean	Std Dev	Skewness	Kurtosis
No put				Infeas	ible: No solut	ion			
0.8-1.1				Infees	ible: No solut	ion			
1.2	0.0488	0.7996	0.0043	0.1473	0.0495	0.0433	0.0688	2.4538	6.5319
1.3	0.2459	0.6007	0.0104	0.1430	0.0495	0.0446	0.0422	2.4319	8.7183

For high thresholds the investor cannot get an acceptable portfolio without puts.

Raising the threshold further

Strike w_1 w_2 w_3 w_4 $Pr[r < H]$ Mean Std Dev Skewness No put Infeasible: No solution 0.8-1.2 1.3 0.0489 0.7514 0.0043 0.1954 0.0495 0.0372 0.0431 3.6502 Panel $F: H = 2\%, \alpha = 0.05$ LowRisk MedRisk HighRisk LongPut Portfolio Return Moments Strike w_1 w_2 w_3 w_4 $Pr[r < H]$ Mean Std Dev Skewness No put Infeasible: No solution	s	eturn Momen	Portfolio Re			LongPut	HighRisk	MedRisk	LowRisk	
0.8-1.2 1.3 0.0489 0.7514 0.0043 0.1954 0.0495 0.0372 0.0431 3.6502 Panel $F: H = 2\%, \alpha = 0.05$ LowRisk MedRisk HighRisk LongPut Portfolio Return Moments Strike w_1 w_2 w_3 w_4 $Pr[r < H]$ Mean Std Dev Skewness No put Infeasible: No solution	Kurtosis				Pr[r < H]	7 d / 2 d				Strike
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$				ion	ible: No soluti	Infeas				No put
Panel $F: H = 2\%, \alpha = 0.05$ LowRisk MedRisk HighRisk LongPut Portfolio Return Moments Strike w_1 w_2 w_3 w_4 $Pr[r < H]$ Mean Std Dev Skewness No put Infeasible: No solution				ion	ible: No soluti	Infoas				0.8-1.2
	16.0972	3.6502	0.0431	0.0372	0.0495	0.1954	0.0043	0.7514	0.0489	1.3
Strike w_1 w_2 w_3 w_4 $Pr[r < H]$ Mean Std Dev Skewness No put Infeasible: No solution					$2\%, \alpha = 0.05$	anel $F: H =$	P			
No put Infeasible: No solution	s	turn Momen	Portfolio Re			LongPut	HighRisk	MedRisk	LowRisk	
	Kurtosis	Skewness	Std Dev	Mean	Pr[r < H]	w ₄	w_3	w_2	w_1	Strike
0.9.1.9 Infrarible Na valution				ion	ible: No soluti	Infeas				No put
0.6-1.5 Inteasible: No solution				ion	ible: No soluti	Infeas				0.8-1.3
1.4 0.0497 0.7015 0.0012 0.2476 0.0496 0.0329 0.0228 6.0207	46.3634	6.0207	0.0228	0.0329	0.0496	0.2476	0.0012	0.7015	0.0497	1.4

Calls give better portfolios

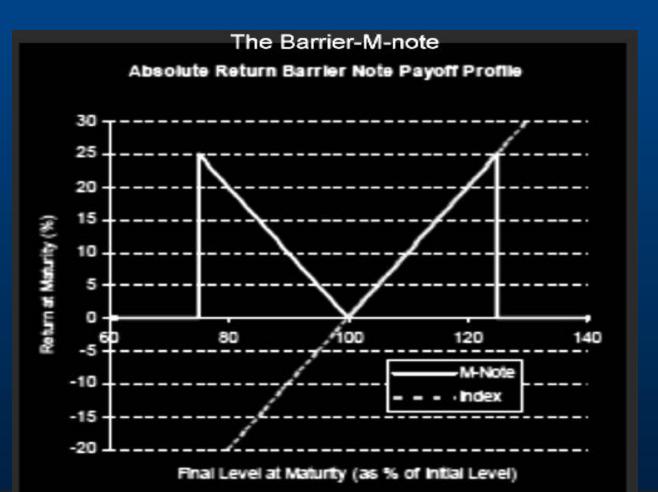
			Pane	B: H =	$-10\%, \alpha =$	5%			
	LowRisk	MedRisk	HighRisk	LongCall		Po	rtfolio R	eturn Mor	nents
Strike	w_1	w_2	w_3	w_4	Pr[r < H]	Mean	Std Dev	Skewness	Kurtosis
No Call	0.5871	0.2052	0.2077	0.0000	0.0498	0.1018	0.1226	0.0000	0.0000
0.8	0.7419	0.0027	0.1524	0.1030	0.0496	0.1081	0.1296	0.1186	-0.1196
0.9	0.7968	0.0008	0.1005	0.1019	0.0496	0.1063	0.1395	0.3934	-0.1643
1	0.6978	0.1000	0.1498	0.0514	0.0496	0.1072	0.1403	0.4424	0.0592
1.1	0.7954	0.0032	0.1483	0.0531	0.0497	0.1043	0.1546	0.9297	1.0514
1.2	0.5948	0.1995	0.2017	0.0040	0.0495	0.1019	0.1244	0.0817	0.0479

Improvement is greater than 60 bps!

Using collars

			H = -10%	$\alpha = 0.05$				
	LowRisk	MedRisk	HighRisk	Collar		Portfolio R	eturn Mome	nts
Strike	w_1	w_2	w_3	w_4	Mean	Std Dev	Skewness	Kurtosis
No collar	0.5871	0.2052	0.2077	-	0.1018	0.1226	0.0000	0.0000
$K_c = 1.0, K_p = 1.0$	0.5986	0.1998	0.2001	0.0015	0.1035	0.1241	0.0000	0.0000
$K_c = 1.05, K_p = 0.95$	0.5991	0.1983	0.2002	0.0015	0.1027	0.1234	0.0069	0.0078
$K_c = 1.0, K_p = 0.8$	0.7984	0.0014	0.1494	0.0507	0.1060	0.1363	0.3236	0.1361
$K_c=0.9, K_p=0.7$	0.6880	0.1007	0.1551	0.0562	0.1062	0.1302	0.1630	-0.0727
$K_c=0.8, K_p=0.7$	0.7354	0.0068	0.2039	0.0539	0.1056	0.1225	0.0215	-0.0148

Barrier M-note



Parsing the M-note

$$r_4 = \begin{cases} |r_2| & \text{if } |r_2| \le 0.25 \\ 0 & \text{if } |r_2| > 0.25 \end{cases}$$

			1	$I = -10\%, \alpha :$	= 0.05				
	LowRisk	MedRisk	HighRisk	Long Note		19	Portfolio Re	eturn Momer	nts
Strike	w_1	w_2	w3	2014	Pr[r < H]	Mean	Std Dev	Skewness	Kurtosis
No note	0.5871	0.2052	0.2077	8	0.0498	0.1018	0.1226	0.0000	0.0000
Barrier: ±0.25	0.0009	0.0426	0.2635	0.6929	0.0495	0.1237	0.1405	0.0131	0.0048

Return pick-up greater than 250 bps!

$$\begin{split} &CON_{call}[\text{Strike} = 1 + M] = e^{-rT}N\left[\frac{\ln(1/(1+M)) + (r - \sigma^2/2)T}{\sigma\sqrt{T}}\right] \\ &CON_{put}[\text{Strike} = 1 - M] = e^{-rT}N\left[-\left(\frac{\ln(1/(1-M)) + (r - \sigma^2/2)T}{\sigma\sqrt{T}}\right)\right] \end{split}$$

Underfunded Portfolios

See: Das, S., Kim, S., Statman, M., (2014). "Coming up Short: Managing Underfunded Portfolios in an LDI-ES Framework" (*Journal of Portfolio Management*).

Four remedies:

- Cash infusions from sponsors (W).
- Increase horizons, postpone terminal date (T).
- Increase shortfall tolerance, i.e., take more risk (K).
- Reducing targets (H).

Sample remedies

Here, we consider an investor standing at time j = 4 with a beginning-of-period wealth equal to 44% of his desired threshold of \$1,000,000 (i.e., $W_{j-1}/H = 0.44$). The expected return on the risky asset each period is $\mu_j = 0.07$, with a standard deviation of $\sigma_j = 0.20$, and the risk-free rate of $r_j = 0.03$ per annum.

Remedy	Change	K	H	K/H	N	W_{μ_1}	W_{μ}/H	мj [‡]
Panel A: Origin	al <i>K/H</i> = 15%, (Original N = 2	O years		X	1		
Do nothing	<u> </u>	\$150,000	\$1,000,000	15%	20	\$440,000	0.4400	infeasible
Increase W _j	\$33,000	\$150,000	\$1,000,000	15%	20	\$473,000	0.4730	0.1465
Increase N	3	\$150,000	\$1,000,000	15%	23	\$440,000	0.4400	0.2077
Increase K	\$39,300	\$189,300	\$1,000,000	18.93%	20	\$440,000	0.4400	0.1959
Decrease H	\$55,100	\$150,000	\$944,900	15.87%	20	\$440,000	0.4657	0.1589
Panel B: Origin	nal <i>IVH</i> = 10%, (Original $N=2$	0 years	1				
Do nothing		\$100,000	\$1,000,000	10%	20	\$440,000	0.4400	infeasible
Increase W	\$75,300	\$100,000	\$1,000,000	10%	20	\$515,300	0.5153	0.0953
Increase N	5	\$100,000	\$1,000,000	10%	25	\$440,000	0.4400	0.0762
Increase K	\$89,300	\$189,300	\$1,000,000	18.93%	20	\$440,000	0.4400	0.1959
Decrease H	\$125,500	\$100,000	\$874,500	11.44%	20	\$440,000	0.5031	0.1104

Underfunded portfolios: lessons

- A conversation about shortfalls must be undertaken in good times to put in place a plan for bad times.
- Unless investors have very stringent shortfall risk thresholds, LDI-ES rebalancing does better for them than fixed-proportion rebalancing.
- Portfolio infusions are not as effective in resolving underfunded situations as other measures, such as increasing risk, cutting back on target liabilities/goals, and extending portfolio horizon.

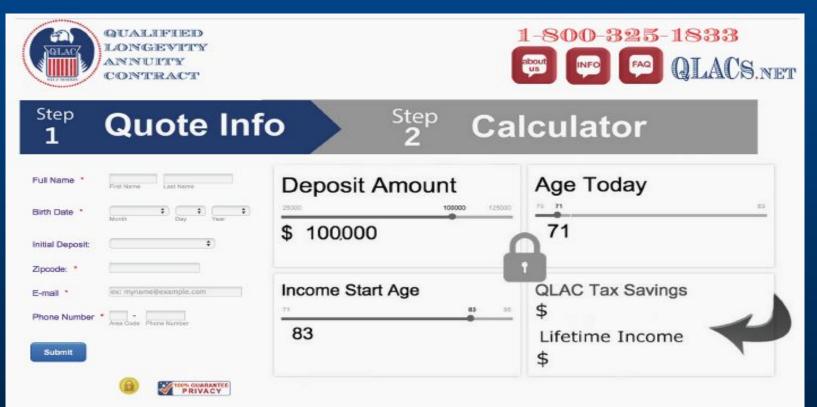
Tax-optimized investing

(Das, Ding, Newell, Ostrov (JIS 2017)

An investor has a portfolio with a stock and cash position that can be traded periodically. The stock is subject to the American taxation system. The portfolio has a given time horizon of T years.

- Basic question: What fraction, f, of the portfolio should be in stock?
- More specifically: What is the optimal static interval [L,U] in which to dynamically maintain f over the portfolio's time horizon?

Managing Longevity Risk



QLAC= QUALIFIED LONGEVITY ANNUITY CONTRACT



As retirees live longer the government has passed a law that allows the lesser of 25% or \$125,000 of your December 31st prior year IRA balance to be invested into a "qualified" longevity annuity contract or QLAC therefore avoiding RMD until the maximum age of 85. This low cost no annual fee deferred income annuity encourages guaranteed lifetime income in retirement.

QLAC Pricing

If you made a lump sum payment of \$125,000		*Annual income amount based on income start age Life Annuity income type						@QLACS.net			
		67 male female		70 male female		75 male female		80 male female		85 male female	
Contract Issue Age	55	\$14,345	\$13,264	\$17,918	\$16,368	\$27,205	\$24,234	\$44,828	\$38,823	\$83,643	\$70,291
	60	\$11,902	\$11,030	\$14,962	\$13,672	\$22,923	\$20,381	\$38,213	\$32,923	\$72,400	\$60,318
	65	\$ 9,565	\$ 8,925	\$12,133	\$11,147	\$19,045	\$16,943	\$32,133	\$27,601	\$61,786	\$51,129
	68	N/A		\$10,555	\$ 9,753	\$16,792	\$15,001	\$28,624	\$24,623	\$55,537	\$45,913
	70	N/A		N/A		\$15,063	\$13,546	\$26,303	\$22,712	\$51,360	\$42,545
	72	N/A		N/A		\$13,580	\$12,314	\$23,953	\$20,826	\$47,152	\$39,257
	75	N/A		N/A		N/A		\$19,966	\$17,663	\$40,738	\$34,382

Reverse Mortgages



3. Can I apply for a HECM even if I did not buy my present house with FHA mortgage insurance?

LEARN MORE

Summary

- The investment landscape is changing on account of low interest rates, low equity premium, longevity, and high volatility.
- Targeting wealth at retirement is being replaced with targeting an income stream, through the lens of Liability-Driven Investing (LDI).
- This is embodied in Goal Based Investing where sub-portfolios for each goal may be optimized, exploiting Mental Accounts in Behavioral
- Portfolio Theory, consistent with Mean-Variance Optimization.
 Structured Products and Annuities / Reverse Mortgages are gaining significant attention and should be part of an investor portfolio, as part of the move from selling Products to selling Solutions.