Methodology of Morningstar's Best Interest Scorecard

How we score rollover recommendations in terms of investment quality, client fit, and service value

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There are no material changes from the previous methodology. Prior to the Medalist launching in May 2023, Morningstar used the Morningstar Analyst Ratings and/or the Morningstar Quantitative Ratings when assessing the fund's Investment Quality. In May 2023, Morningstar combined the Morningstar Analyst Rating and the Morningstar Quantitative Rating into a single, encompassing forward-looking rating, the Morningstar Medalist Rating. The updates reflect the use of Medalist Ratings for Investment Quality assessment and the updates do not constitute a methodology change.

Overview

Morningstar's Best Interest Scorecard is tool to help financial advisors determine if rolling over a client's assets in a defined contribution (DC) plan, such as a 401(k) plan into an account under the advisor's purview, such as an individual retirement account (IRA).

Exhibit 1 presents an overview of the methodology. As it shows, we analyze three portfolios which for short we refer to as *current*, *best*, and *proposed* as follows:

1) *Current*. The portfolio that the investor is currently holding in the DC plan.
2) *Best*. The best portfolio that the investor could create from the options in the DC plan that is consistent with the investors' needs, circumstances, and risk tolerance. We form this portfolio using manager structure optimization as defined by Waring et al. (2000) and Waring and Siegel (2003) and described in Appendix C.
3) *Proposed*. The portfolio that the advisor is proposing for the investor in the rollover account. If there is no score from a risk tolerance questionnaire (RTQ), we assume that this portfolio matched is tailored to the investor's needs, circumstances, and risk aversion. (Otherwise we assume that RTQ score reflects the investor's risk aversion.)

Exhibit 1: Overview of the Methodology of Morningstar's Best Interest Scorecard

As Exhibit 1 shows, each of the three portfolios is subject to five analyzes. Exhibit 2 provides a summary of each. Exhibit 2 describes each analysis in detail.

Exhibit 2: The Five Analyzes of each Portfolio

1. **Investment Quality (Alpha):** Quality and cost of underlying investments.
2. **Asset Allocation Efficiency (Beta):** Overall efficiency of the asset allocation relative to Morningstar's Target Risk Indices.
3. **Risk Appropriateness (Delta):** Compare the ability of the plans to deliver a portfolio that matches the client's risk tolerance.
4. **Financial Planning Services (Gamma):** The value of financial planning services provided. Examples include: savings guidance, life insurance advice, estate planning, asset location, behavioral coaching, rebalancing and annuity purchase decisions.
5. **Other Considerations (Omega):** Other factors to be considered, such as appreciated employer securities, financial health of the investor and employer, desire to work with an advisor, withdrawal accessibility, beneficiary rights, unique investments.

Portfolio Constituents

The best and proposed portfolios consist of managed investments such as open-end funds and exchange traded funds (ETFs). For simplicity, we refer to any managed investment as a fund. The current portfolio can also contain individual stocks which we classify by stock classes:

1. Individual Large-Cap Stock
2. Individual Mid-Cap Stock
3. Individual Small-Cap Stock

Let

ω_{PFi} = portfolio *P*'s allocation to fund *i*

ω_{PSk} = portfolio P's allocation to individual stocks of class *k* (0 for best and proposed portfolios)

ω_{PF} = portfolio *P*'s total allocation to funds

n_P = the number of funds in portfolio *P*

m_S = the number of stock classes

The total allocation to funds is:

$$\boldsymbol{\omega_{PF} = \sum_{i=1}^{n_P} \omega_{PFi}}$$

The total of all of the allocations must be 100%:

$$\boldsymbol{\omega_{PF} + \sum_{k=1}^{m_S} \omega_{PSk} = 1}$$

Some of the analyses done on the current portfolio in the Best Interest Scorecard is done on the part of the portfolio composed of funds. For these analyses, we use the weights of the funds relative to the funds alone:

$$\boldsymbol{w_{PFi} = \frac{\omega_{PFi}}{\omega_{PF}}}$$

<u>Investment Quality (Alpha)</u>

The quality of investments can be thought of as a combination of the investment costs (e.g., expense ratios) and an assessment of the likelihood of the investment strategy outperforming its risk-adjusted peers in the future. While there are a number of potential metrics that could be used to proxy quality, we would use Morningstar’s Medalist Ratings, which is the summary expression of Morningstar's forward-looking analysis of a fund. Morningstar analysts assign the ratings on a five-tier scale with three positive ratings of Gold, Silver, and Bronze, a Neutral rating, and a Negative rating. For those funds that are not fully rated by an actual analyst, we would use a process to estimate the Medalist Rating based on the attributes of the fund (i.e., synthetically create an Medalist Rating).

Exhibit 3 shows how we calculate alpha for each fund in a portfolio. First, we map the Medalist Rating of the fund into a value between +0.50% (Gold) and -0.50% (Negative) and then subtract the fund’s annual expense ratio. We calculate the overall alpha for a portfolio *P* as follows:

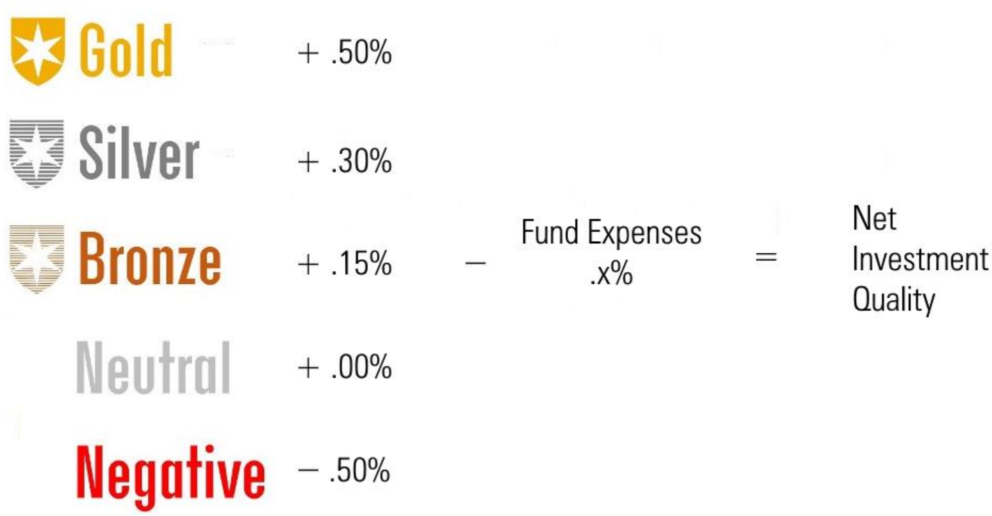
$$\boldsymbol{\alpha_P = \sum_{i=1}^{n_P} w_{PFi}\alpha_{Pi}}$$

where

α_P = the alpha of portfolio *P*

α_{Pi} = the alpha of fund *i* in portfolio *P* calculated according to Exhibit 3.

Exhibit 3: Calculation of Alpha for a Fund from the Medalist Rating and Fund Expenses



The Target Risk Ecosystem

The Beta and Gamma components of the Best Interest Scorecard are derived from an analysis of the risk of each portfolio that we developed to score the riskiness of portfolios of funds using Morningstar's Target Risk Indexes. We call this system the Target Risk Ecosystem. Because DC investors often own company stock in addition, we extend the system here to allow of individual domestic stocks.

Exhibit 4 shows the constituents of the Morningstar Target Risk indexes at the asset class level, plus additional rows to show how we accommodate allocations to individual stocks. In implementation, each asset class in represented by a Morningstar index. The exhibit shows 7 target risk indexes when in in fact Morningstar only has five; namely, Conservative through Aggressive. The Target Risk Ecosystem extends the set to 7 indexes by creating an all fixed income version of Conservative (Ultra Conservative) and a levered version of Aggressive (Ultra Aggressive). The reason for adding these two extreme target risk portfolios is to accommodate a wide range of risk.

The extended family of 7 target risk indexes are numbers 0 through 6. This numbering, as we explain below, forms the basis of the risk score

Estimating the Asset Allocation of each Portfolio

The first step in calculating the risk score is to perform returns-based style analysis (RBSA) on the proposed portfolio and the fund part of the current portfolio. To do this, we calculate the historical monthly returns on the fund part of the portfolio over most recent *T* months (*T* being 48) as follows:

$$R_{PFt} = \sum_{i=1}^{n_P} w_{PFi} R_{PFit}$$

where

R_{PFt}	=	the total return on the fund portfolio in month *t*
R_{PFit}	=	the total return on fund *i* in month *t*

The RBSA model, as formulated by Sharpe (1988, 1992) is:

$$R_{PFt} = \sum_{j=1}^{m_A} x_{PFj} R_{Ajt} + u_{Pt}$$

where

m_A	=	the number of regular asset classes (13 as per Exhibit 4)
x_{PFj}	=	the estimated allocation of the fund part of the portfolio to asset class *j*
R_{Ajt}	=	the total return on the index representing asset class *j* in month *t*
u_{Pt}	=	the part of the fund part of the portfolio in month t not explained by asset allocation

The RBSA model differs the standard linear regression model in that it the estimated coefficients, the x_{PFj}'s, are subject to two constraints:

1. Each coefficient is nonnegative; i.e., each $x_{PFj} \geq 0$
2. The coefficients sum to 100%; i.e., $\sum_{j=1}^{m_A} x_{PFi} = 1$

Due to these constraints, particularly (2), the RBSA model cannot be solved by linear regression. Rather, it must be solved by quadratic programming, as we discuss in Appendix A.

Exhibit 4: Extended Family of the Morningstar Target Risk Indexes

Asset Class	Ultra Conservative (0)	Conservative (1)	Moderately Conservative (2)	Moderate (3)	Moderately Aggressive (4)	Aggressive (5)	Ultra Aggressive (6)
US Large-Cap Stocks	0.00%	9.00%	17.00%	23.00%	29.00%	33.00%	38.21%
US Mid-Cap Stocks	0.00%	3.00%	6.50%	11.00%	14.50%	16.50%	19.11%
US Small-Cap Stocks	0.00%	1.00%	3.00%	5.00%	7.00%	10.00%	11.58%
Developed Markets ex-US Stocks	0.00%	5.00%	9.00%	13.00%	19.50%	23.50%	27.21%
Emerging Markets Stocks	0.00%	2.00%	4.50%	7.00%	9.00%	11.00%	12.74%
REITs	0.00%	0.00%	0.00%	1.00%	1.00%	1.00%	1.16%
Commodities	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Global ex- US Government Bonds	7.50%	6.00%	4.00%	2.00%	0.00%	0.00%	0.00%
TIPS	11.25%	9.00%	6.00%	4.00%	1.00%	0.00%	0.00%
US Long-Term Core Bonds	8.75%	7.00%	6.00%	4.00%	2.50%	0.00%	0.00%
US Intermediate-Term Core Bonds	48.13%	38.50%	30.50%	22.50%	14.50%	5.00%	0.00%
US Short-Term Core Bonds	20.63%	16.50%	11.50%	5.50%	2.00%	0.00%	0.00%
Cash	3.75%	3.00%	2.00%	2.00%	0.00%	0.00%	-10.00%
Individual Large-Cap Stocks	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Individual Mid-Cap Stocks	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Individual Small-Cap Stock	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

<u>Accounting for Company Stock</u>
If the current portfolio contains company stock, we extend the list of asset classes to include individual stocks as shown in the last three rows of Exhibit 4.

We calculate the allocation of the portfolio to each asset class and individual stock class. For the regular asset classes, we use the RBSA weights:

$$x_{Pj} = \omega_{PF} x_{PFj}$$

For the individual stock weights, we use the holdings-based weights:

$$x_{Pm_A+k} = \omega_{PSk}$$

Putting these together, we get a vector of m_A+m_S weights which we denote $\vec{\boldsymbol{x}}_{\boldsymbol{P}}$. The differences between this vector the vectors of the weights of the 7 target risk indexes shown in Exhibit 4 is the basis of the risk score.

<u>Calculating the Risk Score</u>
From the 7 target risk indexes shown in Exhibit 4, we form a continuum of benchmark portfolios. The risk score is a number that indicates where the benchmark associated with it falls. Let S_P denote the risk score of portfolio *P*. It can fall between 0 (100% Ultra Conservative) to 6 (100% Ultra Aggressive). For values between 0 and 6, S_P is broken down between:

ι_P	=	the integer part of S_P
θ_P	=	the fractional part of S_P

So, for example, if S_P = 2.6, ι_P = 2 and θ_P =0.6.

The risk score is the value of S_P that minimizes the distance between the portfolio's asset class and individual stock class allocation vector and that of a benchmark along the target risk continuum. To measure this distance, we need the variance-covariance matrix amount the asset classes and individual stock classes. We denote this matrix $\boldsymbol{V}$. Appendix B explains how we estimate this matrix.

Taking the value of ι as given, the distance between the portfolios weight vector and that of a benchmark along the continuum defined by $S_P = \iota + \theta$ as function of θ is:

$$D_{P\iota}(\theta) = \sqrt{\left(\vec{x}_P - (1-\theta)\vec{x}_{I\iota} - \theta\vec{x}_{I\iota_P+1}\right)'\boldsymbol{V}\left((\vec{x}_P - (1-\theta)\vec{x}_{I\iota} - \theta\vec{x}_{I\iota+1})\right)}$$

where

$\vec{x}_{I\iota}$	=	the weight vector of target risk index ι

$D_{P\iota}(\theta)$ is minimized by the value of θ given by:

$$\hat{\theta}_{P\iota} = \frac{(\vec{x}_{I\iota+1} - \vec{x}_\iota)'\boldsymbol{V}(\vec{x}_P - \vec{x}_\iota)}{(\vec{x}_{I\iota+1} - \vec{x}_i)'\boldsymbol{V}(\vec{x}_{I\iota+1} - \vec{x}_\iota)}$$

We constrain each potential choice for θ_P to be between 0 and 1:

$$\theta_{P\iota} = \begin{cases} 0, & if\ \hat{\theta}_{P\iota} < 0 \\ \hat{\theta}_{P\iota}, & if\ 0 \le \hat{\theta}_{P\iota} \le 1 \\ 1, & \hat{\theta}_{P\iota} > 1 \end{cases}$$

We calculate $\theta_{P\iota}$ for ι=0, 1, …, 5. The one that produces the lowest value of $D_{P\iota}(\theta_{P\iota})$ is ι_P. we calculate the risk score:

$$S_P = \iota_P + \theta_{P\iota_P}$$

The minimal value of $D_{P\iota}(\theta_{P\iota})$ is the *misfit risk* of the portfolio with we denote D_P. The Asset Allocation Efficiency Score (Beta) is based on misfit risk.

Risk Aversion

In the mean variance framework, a common way of defining expected utility is as a linear function of expected return and variance of the portfolio:

$$U_P = \mu_P - \frac{\lambda}{2}\sigma_P^2$$

Where

U_P = the expected utility of the portfolio
μ_P = the expected return of the portfolio
λ = the risk aversion parameter of the investor
σ_P^2 = the variance of the portfolio

We estimate λ, from a benchmark risk score, S_{BM}, depending on whether or not a RTQ score is available. These methods are as follows:

If there is an RTQ Score

The RTQ score should be an equity allocation between 0% and 100%. We map it into the benchmark risk score using the equity allocations as breakpoints a piecewise linear function. Exhibit 5 shows the equity breakpoints and corresponding risk scores based on the extend family of Morningstar Target Risk Indexes.

Exhibit 5: Breakpoints of the Function Mapping RTQ Equity Allocations to Risk Scores

Equity Allocation	Risk Score
0%	0
20%	1
40%	2
60%	3
80%	4
95%	5
110%	6

If the RTQ equity allocation, eq_{RTQ} falls between equity breakpoints eq_j and eq_{j+1}, the benchmark risk falls between the corresponding risk scores S_j and S_{j+1}. The provisional benchmark risk score is:

$$\hat{S}_{BM} = \frac{eq_{j+1} - eq_{RTQ}}{eq_{j+1} - eq_j} S_j + \frac{eq_{RTQ} - eq_j}{eq_{j+1} - eq_j} S_{j+1}$$

If there is no RTQ score

If there is no RTQ score, we assume that the portfolio on the target risk continuum identified by the risk score of the advisor proposed portfolio is optimal for the investor. Based on this assumption, we use the risk score of advisor proposed portfolio as the provisional benchmark risk score, $\hat{S}_{BM}$.

To avoid extreme values for the implied value of λ at the Ultra Conservative end of the target risk continuum, for the benchmark risk score, we use:

$$S_{BM} = max(\hat{S}_{BM}, 0.5)$$

Calculating the Risk Aversion Parameter from the Benchmark Risk Score

By decomposing a risk score into its integer and fractional components, $S=\iota+\theta$, we can identify which segment of the target risk continuum the optimal portfolio is on (the segment from ι to ι_{+1}) and exactly where it is between the ends of those segments (θ towards $\iota+1$). However, because the risk score is bound between 0 and 6 and we need to express location of the optimal portfolio as being located between a pair of consecutive target indexes, when $S=6$, we set $\iota=5$ and $\theta=1$.

We treat the target risk continuum as an efficient frontier. The variance-covariance matrix fore this frontier is the part of $\boldsymbol{V}$ that covers the asset classes. We denote that as $\boldsymbol{V_A}$. The expected returns are those for the asset classes derived using "reverse optimization" as described in Appendix B. We denote the vector of these as $\vec{\mu}_A$.

Given that we know which segment of the target risk frontier the optimal portfolio is on, we express utility as a function of θ.

$$U(\theta) = \mu(\theta) - \lambda Q(\theta)$$

where

$$\mu(\theta) = [(1-\theta)\vec{x}_{I_\iota} + \theta\vec{x}_{I_{\iota+1}}]'\vec{\mu}_A$$

$$Q(\theta) = \frac{1}{2}[(1-\theta)\vec{x}_{I_\iota} + \theta\vec{x}_{I_{\iota+1}}]'\boldsymbol{V_A}[(1-\theta)\vec{x}_{I_\iota} + \theta\vec{x}_{I_{\iota+1}}]$$

Let

$$\mu_\iota = \vec{x}'_{I_\iota}\vec{\mu}_A$$

$$\mu_{\iota+1} = \vec{x}'_{I_{\iota+1}}\vec{\mu}_A$$

$$\sigma_\iota^2 = \vec{x}'_{I_\iota}\boldsymbol{V_A}\vec{x}_{I_\iota}$$

$$\sigma_{\iota+1}^2 = \vec{x}'_{I_{\iota+1}}\boldsymbol{V_A}\vec{x}_{I_{\iota+1}}$$

$$\sigma_{\iota,\iota+1} = \vec{x}'_{I_\iota}\boldsymbol{V_A}\vec{x}_{I_{\iota+1}}$$

This lets us write the expected return and risk functions as follows:

$$\mu(\theta) = (\mu_{\iota+1} - \mu_\iota)\theta + \mu_\iota$$

$$Q(\theta) = \frac{1}{2}\left(\sigma_\iota^2 + \sigma_{\iota+1}^2 - 2\sigma_{\iota,\iota+1}\right)\theta^2 + \left(\sigma_{\iota,\iota+1} - \sigma_\iota^2\right)\theta + \frac{1}{2}\sigma_\iota^2$$

For θ to be optimal, we need $U'(\theta)=0$. Therefore, it follows that:

$$\lambda = \frac{\mu'(\theta)}{Q'(\theta)}$$

Since,

$$\mu'(\theta) = \mu_{\iota+1} - \mu_{\iota}$$

$$Q'(\theta) = \left(\sigma_{\iota}^2 + \sigma_{\iota+1}^2 - 2\sigma_{\iota,\iota+1}\right)\theta + \sigma_{\iota,\iota+1} - \sigma_{\iota}^2$$

So, to calculate the risk aversion coefficient associated with the benchmark risk score, we decompose the risk score into its integer (ι) and fractional (θ) components and calculate:

$$\lambda = \frac{\mu_{\iota+1} - \mu_{\iota}}{\left(\sigma_{\iota}^2 + \sigma_{\iota+1}^2 - 2\sigma_{\iota,\iota+1}\right)\theta + \sigma_{\iota,\iota+1} - \sigma_{\iota}^2}$$

Once we have calculated λ based on the proposed portfolio, we use it to calculated the best portfolio from the plan lineup using the methodology described in Appendix C. We then perform RBSA on it and calculate its risk score using the method described above.

Asset Allocation Efficiency (Beta)

We use the misfit risk from the Target Risk Ecosystem to measure how inefficient the asset allocation of each portfolio. In the case of the current portfolio, misfit risk could include inefficiencies dues to holding company stock. We use the risk aversion parameter that we infer from the advisor proposed portfolio, λ, to convert misfit risk into a component of expected utility:

$$\beta_P = -M\frac{\lambda}{2}D_P^2$$

Where M is the *fit-to-client multiplier*. This is parameter that allows us to adjust the importance of the fit-to-client measures β and δ, in the overall scores.

Risk Appropriateness (Delta)

We calculate the appropriateness of the risk level of the plan portfolios by comparing the expected utility of the custom benchmark of each portfolio to the utility of the custom benchmark of the advisor proposed portfolio. Given portfolio P's risk score, $S_P = \iota_P + \theta_P$, the custom benchmark is:

$$\vec{x}_{PB} = (1 - \theta_P)\vec{x}_{A\iota_P} + \theta_P\vec{x}_{A\iota_{P+1}}$$

The benchmark portfolio associated with the benchmark risk score is:

$$\vec{x}_{BM} = (1 - \theta_{BM})\vec{x}_{A\iota_{BM}} + \theta_{BM}\vec{x}_{ABM_{P+1}}$$

We calculate the expected return and variance of each benchmark portfolio:

$$\mu_{PB} = \vec{x}'_{PB}\vec{\mu}_A$$

$$\sigma_{PB}^2 = \vec{x}'_{PB}\boldsymbol{V_A}\vec{x}_{PB}$$

As well as the expected return of the benchmark portfolio associated with the benchmark risk score:

$$\mu_{BM} = \vec{x}'_{BM}\vec{\mu}_A$$

$$\sigma_{BM}^2 = \vec{x}'_{BM}\boldsymbol{V_A}\vec{x}_{BM}$$

The utility of each portfolio benchmark is:

$$U_{PB} = \mu_{PB} - \frac{\lambda}{2}\sigma_{PB}^2$$

And the utility of the benchmark portfolio associated with the benchmark risk score is:

$$U_{BM} = \mu_{BM} - \frac{\lambda}{2}\sigma_{BM}^2$$

The Delta measure of each portfolio's the utility of the custom benchmark, relative to that of benchmark associated with the benchmark risk score:

$$\delta_P = M(U_P - U_{BM})$$

Note that if there is no RTQ score, U_{BM}=U_{Prop} so that δ_{Prop}=0.

Financial Planning Services (Gamma)

We identify a number of advice services that could come with each portfolio:

- Savings Guidance
- Insurance Planning
- Estate Planning
- Tax Efficient Investing
- Retirement Withdrawal Planning
- Pension Optimization
- Annuity Planning
- Retirement Age Guidance
- Total Wealth Asset Allocation
- Behavioral Coaching
- Rebalancing

Based upon research conducted by Morningstar and other organization, we assign values to each of services over 5 lifecycle stages with respect to retirement. Let *ytr* be the number of years to retirement, the 5 stages are:

- Early Accumulation ($ytr \geq 26$)
- Mid Accumulation ($11 \leq ytr \leq 25$)
- Transition ($0 \leq ytr \leq 10$)
- Early Retirement ($-15 \leq ytr \leq -1$)
- Late Retirement ($ytr \leq -16$)

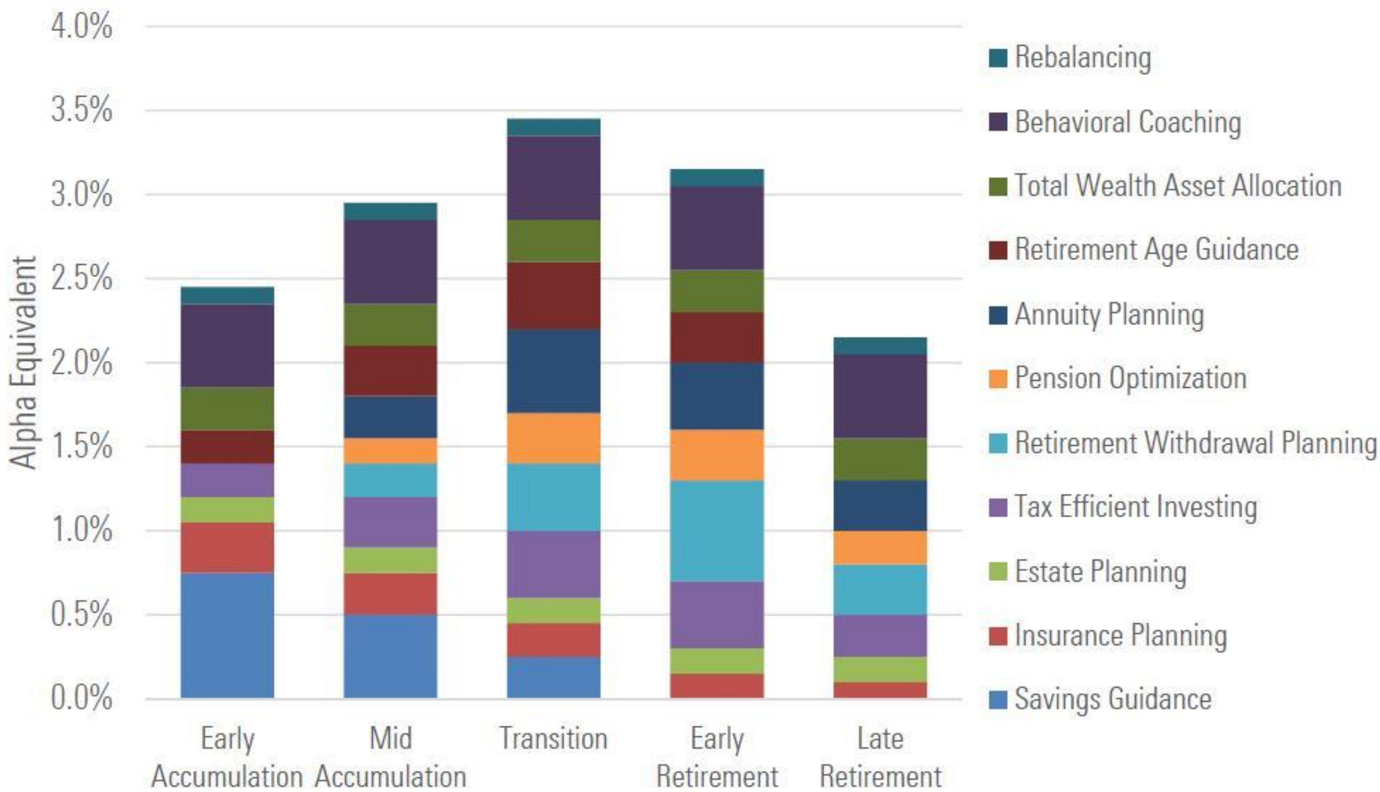
We calculate *ytr* as retirement age — current age.

Exhibit 6 shows the value that we assign to each service at each stage. Exhibit 7 shows these values graphically.

Exhibit 6: Values of Financial Services: Data

Service	Early Accumulation	Mid Accumulation	Transition	Early Retirement	Late Retirement
Savings Guidance	0.75%	0.50%	0.25%	0.00%	0.00%
Insurance Planning	0.30%	0.25%	0.20%	0.15%	0.10%
Estate Planning	0.15%	0.15%	0.15%	0.15%	0.15%
Tax Efficient Investing	0.20%	0.30%	0.40%	0.40%	0.25%
Retirement Withdrawal Planning	0.00%	0.20%	0.40%	0.60%	0.30%
Pension Optimization	0.00%	0.15%	0.30%	0.30%	0.20%
Annuity Planning	0.00%	0.25%	0.50%	0.40%	0.30%
Retirement Age Guidance	0.20%	0.30%	0.40%	0.30%	0.00%
Total Wealth Asset Allocation	0.25%	0.25%	0.25%	0.25%	0.25%
Behavioral Coaching	0.50%	0.50%	0.50%	0.50%	0.50%
Rebalancing	0.10%	0.10%	0.10%	0.10%	0.10%

Exhibit 7: Values of Financial Services: Chart



Let

I_{Pk}	=	indictor showing whether or not service *k* is offered with portfolio *P*. 1 if yes, 0 is no.
$\Gamma_k(ytr)$	=	value of service k given *ytr* years to retirement
N	=	number of services
$PlFee_P$	=	plan fee associated with portfolio *P*
$AdFee_P$	=	advisory free associated with portfolio *P*

The Financial Planning Services Score of each portfolio is:

$$\gamma_P = \sum_{k=1}^{N} I_{Pk}\Gamma_k(ytr) - PlFee_P - AdFee_P$$

<u>Other Considerations (Omega)</u>

There are a variety of things that should be considered before deciding to roll money out of a 401(k) that are not easy to put into an "alpha" context. Therefore, these are things that should be documented (e.g., via a checklist) before reaching any final rollout decision, such as:

- Does the DC plan account hold appreciated employer securities? (> NUA)
- Is the client near bankruptcy? Does the client have high risk assets/occupation subject to litigation?
- Is the plan sponsor/employer at risk to file bankruptcy or go out of business?
- Does the investor have a desire to work with an advisor? (i.e., does the investor think the advisor will help ensure he/she/they achieve their goals?)
- What is the withdrawal and beneficiary friendliness in the DC plan?
- Are there unique investments (or other services) in the DC plan that should be considered before completely rolling out of the plan?
- Does the investor want to consolidate accounts?
- Does the investor have a strong desire to leave/stay in the DC plan?

Currently, while we collect whether or not these are issues, we do not score these items.

<u>Scoring</u>

For each of the four scores, we calculate how much of the advisor proposed portfolio (*Prop*) is an improvement over the plan portfolios, Current (*Cur*) and *Best*:

$$\alpha_{Imp} = \alpha_{Prop} - max(\alpha_{Cur}, \alpha_{Best})$$
$$\beta_{Imp} = \beta_{Prop} - max(\beta_{Cur}, \beta_{Best})$$
$$\gamma_{Imp} = \gamma_{Prop} - max(\gamma_{Cur}, \gamma_{Best})$$
$$\delta_{Imp} = \delta_{Prop} - max(\delta_{Cur}, \delta_{Best})$$

When displaying these scores, beta and delta are first added together to display the fit-to-client score.

These calculations are for display purposes only and do not factor in the recommendation. For that, we calculate the overall Best Interest Score (*BIS*) for each portfolio and the improvement in it:

$$BIS_P = \alpha_P + \beta_P + \gamma_P + \delta_P$$

$$BIS_{Imp} = BIS_{Prop} - max(BIS_{Cur}, BIS_{Best})$$

The value of BIS_{Imp} determines the recommendation as follows:

$$Recommendation = \begin{cases} Stay, & BIS_{Imp} < 0 \\ Caution, & 0 \leq BIS_{Imp} \leq 0.005 \\ Rollout, & BIS_{Imp} > 0.005 \end{cases}$$

The intermediate results and related calculations for display can be presented in a user interface. Note that we do not recommend showing the values, but rather that the elements of the display be color coded. This color coding could be based on breakpoints as -0.01, 0, and 0.005.

Appendix A: Solving the Returns-Based Style Model

To perform RBSA on the portfolio returns, we first need to estimate the covariance of the returns on the fund part of the portfolio with the returns on each asset class index. To do this, we first need to calculate the average portfolio return:

$$\bar{R}_{PFT} = \frac{1}{T}\sum_{t=1}^{T} R_{PFt}$$

where *T* is the number of months being used in RBSA which is currently 48. Returns are in decimal form so 3% is 0.03.

We also need the average return for each asset class index:

$$\bar{R}_{AjT} = \frac{1}{T}\sum_{t=1}^{T} R_{Ajt}$$

For each asset class *j*, the estimated covariance is:

$$c_{jT} = \frac{1}{T-1}\sum_{h=1}^{H}\left(R_{Ajt} - \bar{R}_{AiT}\right)\left(R_{PFt} - \bar{R}_{PFT}\right)$$

We stack these into a covariance vector, $\vec{c}_T$.

For RBSA, we need to estimate the asset class variance-covariance matrix over *H* months. We estimate the covariance between asset classes *i* and *j* using the sample covariance:

$$V_{AijT} = \frac{1}{T-1}\sum_{t=1}^{T}\left(R_{Ait} - \bar{R}_{AiT}\right)\left(R_{Ajt} - \bar{R}_{AjT}\right)$$

We denote the variance-covariance matrix of the asset class indexes over *T* months as $\boldsymbol{V_{AT}}$.

RBSA is carried out using quadratic programming:

$$\min_{\vec{x}_{PF}} \tfrac{1}{2}\vec{x}_P' \boldsymbol{V_{AT}} \vec{x}_P - \vec{c}\vec{x}_P \; s.t. \sum_{i=1}^{n} x_{PFi} = 1, \vec{x}_{PF} \geq 0$$

The solution to this problem, $\vec{x}_{PF}$, is the vector of RBSA weights on the fund part of portfolio *P*. This problem can be solved using the algorithm presented in Sharpe (1978), or any other quadratic programming algorithm.

Appendix B: The Variance-Covariance Matrix and Expect Returns of the Asset Classes

Estimating the Covariance Matrix of the Asset Class Indexes
In contrast to the estimation of the covariance matrix for RBSA, which uses a rolling 48-month window, for the covariance matrix, the data window for the matrix used everywhere else in the Target Risk Ecosystem and the Best Interest Scorecard has a fixed starting point, January 2002. Thus, this data window grows each time these models are updated. Letting *H* denote the number of months in the estimation period, the averages of the asset class index returns over the full period is given by:

$$\bar{R}_{Aj} = \frac{1}{H}\sum_{t=1}^{H} R_{Ajt}$$

We then estimate the covariance between asset classes *i* and *j* using the sample covariance:

$$V_{Aij} = \frac{12}{H-1}\sum_{t=1}^{H}(R_{Ait} - \bar{R}_{Ai})(R_{Ajt} - \bar{R}_{Aj})$$

These are the elements of $\boldsymbol{V_A}$. Note that we annualize the full period covariance matrix by multiplying by 12.

Expected Returns of the Asset Classes
In order to make the target risk continuum as much like a mean-variance efficient frontier as possible, we do not use external capital market assumptions to set the expected returns in the Target Risk Ecosystem or in the Best Interest Scorecard methodology. Rather, we use the reverse optimization technique. In reverse optimization, we assume that a given portfolio is efficient and derive a set of expected returns that is consistent with that assumption. Since the Moderate target risk index is at the center of the target risk continuum, we use it to perform the reverse optimization.

The first step is to calculate the systematic risk of each asset class with respect to the given portfolio. The vector of systematic risk measures is given by:

$$\vec{b} = \frac{\boldsymbol{V_A}\vec{x}_{A3}}{\vec{x}'_{A3}\boldsymbol{V_A}\vec{x}_{A3}}$$

The expected return is a linear function of systematic risk:

$$\mu_{Aj} = \mu_0 + rp \cdot b_j$$

To solve for μ_0 (expected return for zero systematic risk) and *rp* (the risk premium), we select values for μ_{m_A} and μ_1 and solve:

$$rp = \frac{\mu_{m_A} - \mu_1}{b_{m_A} - b_1}$$

$$\mu_0 = \mu_{m_A} - rp \cdot b_{m_A}$$

We then use the linear function to set the remaining asset class expected returns.

<u>Variances and Covariances for Company Stock</u>

The variance-covariance matrix of the asset classes, $\boldsymbol{V_A}$, is part of the variance-covariance matrix whole variance-covariance, $\boldsymbol{V}$. Hence for all asset class pairs, *i,j*, we have:

$$V_{ij} = V_{Aij}$$

For company stock of class *k*, we assume a signal factor model of returns:

$$R_{Skt} = A_k + B \cdot R_{Akt} + \varepsilon_{kt}$$

where

R_{Skt}	=	the monthly total return on individual stocks of class *k*
A_k	=	the intercept term
B	=	the slope term which we assume to be 1.5
R_{Akt}	=	the monthly total return on asset class *k*
ε_{kt}	=	the error term which is statistically independent of all other random variables

Note from Exhibit 4 that the individual stock classes are aligned with their corresponding asset classes so that:

1. With k=1, R_{A1t} = return on US Large-Cap Stocks, and R_{S1t} = return on Individual Large-Cap Stocks
2. With k=2, R_{A2t} = return on US Mid-Cap Stocks, and R_{S2t} = return on Individual Mid-Cap Stocks
3. With k=3, R_{A3t} = return on US Small-Cap Stocks, and R_{S3t} = return on Individual Small-Cap Stocks

From the single factor model, it follows that the covariance between the return on individual stock class *k* and asset class *j* is:

$$V_{j m_A + k} = B \cdot V_{jk}$$

The covariance between individual stock classes *k* and *q*, $k \neq q$ is:

$$V_{m_A + k m_A + q} = B^2 \cdot V_{kq}$$

We assume that the standard deviation of each individual stock class is a multiple of the standard deviation of its corresponding asset class. Letting *M* denote this multiple (which we set to 2), we have:

$$V_{m_A + k m_A + k} = M^2 \cdot V_{kk}$$

Appendix C: Constructing the Best-in-Plan Portfolio Using Manager Structure Optimization

Manager Structure Optimization

Waring et al. (2000) and Waring and Siegel (2003) present an optimization technique for combining managed investments (open-end mutual funds, ETFs, closed-end funds, etc.), all of which we refer to as funds, into efficient portfolios. In this framework, called manager structure optimization (MSO), risk is tracking error from a pre-specified asset allocation target, and reward is portfolio alpha.[1]

The inputs to MSO are as follows:

$\vec{x}_T$	=	*m*-element vector giving the target asset allocation
$\boldsymbol{X}$	=	*n*×*m* matrix of asset class exposures of *n* funds
ω_i	=	standard deviation of the idiosyncratic part of return on fund *i*
$\boldsymbol{V_A}$	=	the covariance matrix of asset class returns
$\vec{\alpha}$	=	*n*-element vector of the alphas of the funds
λ_{TE}	=	tracking-error aversion parameter

The MSO problem is to select a vector of fund weights, $\vec{w}$, to solve the following maximization problem:

$$\underset{\vec{w}}{max}\ \vec{w}'\vec{\alpha} - \frac{\lambda_{TE}}{2}[(\boldsymbol{X}'\vec{w} - \vec{x}_T)'\boldsymbol{V_A}(\boldsymbol{X}'\vec{w} - \vec{x}_T) + \boldsymbol{\Omega}], s.t. \vec{w} \geq 0, \sum_{i=1}^{n} w_i = 1$$

where $\boldsymbol{\Omega}$ is the *n*×*n* diagonal matrix of ω_i^2's.

The MSO problem can be written and solved as a conventional quadratic programming problem:

$$\underset{\vec{w}}{max}\ \frac{1}{2}\vec{w}'\boldsymbol{V_F}\vec{w} - \vec{w}'\vec{f}, s.t. \vec{w} \geq 0, \sum_{i=1}^{n} w_i = 1$$

where:

$$\boldsymbol{V_F} = \boldsymbol{X}\boldsymbol{V_A}\boldsymbol{X}' + \boldsymbol{\Omega}$$

$$\vec{f} = \boldsymbol{X}\boldsymbol{V_A}\vec{x}_T + \frac{1}{\lambda_{TE}}\vec{\alpha}$$

[1] In Waring et al. (2000), the reward includes a term involving expected returns on asset classes. However, in footnote 16, Waring and Siegel correct an error in this term and state that "[i]f the risk and return assumptions are all estimated so that they fall in a common security market line, this is a zero term." This is the approach that we take. Hence the form of MSO that we use is also called alpha-tracking error optimization.

Inputs for Calculating the Best Portfolio using the Plan Lineup

We calculate the best portfolio using MSO with the following inputs:

Target Asset Allocation ($\vec{x}_T$)

For the target asset allocation, we use the benchmark along the target risk continuum associated with the risk score of the proposed portfolio.

Matrix of Fund Asset Class Exposures (X)

We estimate the asset class exposure of each fund in the plan lineup by running RBSA on each fund. The resulting vectors of asset class weights form the rows of *X*.

The Standard Deviation of the Idiosyncratic Part of Return on Each Fund (The ω_i's)

After running RBSA on each fund, we calculate the time series of residuals:

$$u_{it} = R_{it} - \sum_{j=1}^{m} x_{ij} R_{Ajt}$$

where

u_{it}	=	the residual of fund *i* in month *t*
R_{it}	=	the return on fund *i* in month *t*
x_{ij}	=	the RBSA weight of fund *i* on asset class *j*
R_{Ajt}	=	the return on asset class index *j* in month *t*

We estimate ω_i using the sample standard deviation of the residuals and annualize:

$$\omega_i = \sqrt{\frac{12 \sum_{t=1}^{T} (u_{it} - \bar{u}_i)^2}{T - 1}}$$

where *T* is the number of months used in RBSA (48) and $\bar{u}_i$ is the sample average of the residual:

$$\bar{u}_i = \frac{\sum_{t=1}^{T} u_{it}}{T}$$

The Covariance Matrix of Asset Class Returns ($\boldsymbol{V_A}$*)*
This is the asset class covariance matrix, $\boldsymbol{V_A}$, described in Appendix B.

Vector of the Alphas of the Funds ($\vec{\alpha}$*)*
We form this vector by calculating the alpha of each fund in the manner described in the main body of this document.

Tracking-error aversion parameter (λ_{TE}*)*
We set the tracking-error aversion parameter to a fixed multiple of the risk-aversion parameter which is derived from the risk score of the proposed portfolio (λ):

$$\lambda_{TE} = TEM \cdot \lambda$$

where *TEM* is the tracking error multiplier. We currently set *TEM* to 6.

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