Introduction

Target maturity funds (TMFs) are increasingly popular investment options in retirement plans. TMFs automatically allocate an investor's wealth into a diversified set of asset classes and systematically reduce investment risk as the TMF approaches its target maturity year. According to Greenwich Associates, a leading institutional financial services research consultancy, 80% of large companies now offer TMFs in their 401(k) plans. Furthermore, 34% of corporations automatically enroll employees into 401(k) plans, more than half of which invest in a target-date fund.

Despite the ease of deployment and adoption for investors, TMFs are complex investing instruments. For most investors, critical analysis of TMFs is best left to the experts, in most cases the plan sponsor. Plan sponsors are being offered a growing number of TMF options, including both proprietary TMF solutions and custom TMF methodology overlays created on top of existing plan fund options. As plan sponsors contemplate the numerous options, they need to consider a number of key questions, including the following:

• How do I benchmark the performance of a TMF manager?
• How does a particular TMF compare to another?
• How do I compare the TMF asset allocation glide path and relative risk and return to the industry average for all TMF families?
• What should be the expected risk and return going forward for a particular TMF?
• What is the performance attribution of a TMF manager in terms of market timing and selection returns relative to a passive benchmark glide path?

Until now, there has been no objective way for investors to obtain answers to these questions. A number of firms, such as Dow Jones, Zacks, Target Date Analytics, and Morningstar, have tried to create solutions including the creation of TMF benchmark index candidates. For example,
one firm has created a process that generates its own hypothetical TMF indices and calculates a backward-looking historical TMF risk measure based on its own derived ideal reference glide paths for all TMFs. This approach does not yield indicators of forward-looking expected risk for existing investments such as TMFs that are designed to change their asset allocation purposefully over time.

Unfortunately, all of the above target maturity benchmark index candidates are based on proprietary methodologies using the asset allocation glide path models of each of the respective index publishers. These TMF benchmark index candidates are not derived from actual investable vehicles in the market as is the case with traditionally appropriate benchmark indices for investments. None of the current TMF benchmarking attempts provides the objectivity and transparency that are truly needed to answer significant questions about target maturity funds.

**Target Maturity Industry Benchmarking**

Business Logic has created a patent-pending method and set of objective market-based TMF industry benchmarks to answer all of the questions raised above. This method first generates a set of custom benchmarks, each of which tracks the specific investment strategy execution of each TMF family. The method then aggregates all the custom benchmarks to generate a set of TMF industry average benchmarks.

The target maturity benchmarking problem is broken into multiple steps. To evaluate the passive performance, this method compares the custom benchmark for any TMF family to the TMF industry average benchmark(s). To evaluate active performance, this method compares TMF managers to their custom benchmark.

The Business Logic target maturity benchmarking solution extends the popular returns-based style analysis (RBSA) technique to create glide path style analysis (GPSA), which allows a TMF family’s investment strategy to be projected onto any passive asset class palette. This paper shows that the GPSA method explains more than 95% of the variance of the returns history of the popular TMF families. The GPSA results provide unprecedented transparency of the behavior of TMF fund managers.

The GPSA investment strategy serves as a custom passive benchmark for each TMF family. Furthermore, custom benchmark results for all TMF families are averaged to create a new TMF industry average benchmark. This GPSA market-based target maturity industry benchmark then serves as the legitimate, unbiased, and objective reference point to evaluate the investment strategy and performance of each TMF family.

**Target Maturity Performance Metrics**

The GPSA solution introduces new risk and reward measures that provide quantitative measures for TMF benchmarking and comparison purposes.

A well-known measure of relative investment risk is beta, which is the degree to which an investment varies relative to its appropriate market benchmark. Because TMFs purposefully change their asset allocation over time the traditional concept of beta cannot be used for TMFs. GPSA provides many new glide path–related statistics, including ones that serve as measures of glide path expected risk and performance attribution for any TMF family relative to an industry average TMF benchmark glide path. Some of the GPSA risk and reward measures are summarized below.

1. **Years-to-Target (YTT) Beta**
   For each year-to-target asset allocation of a TMF glide path, GPSA calculates the glide path’s annual beta. Thus, we can answer the specific question of how risky a particular TMF “N” years from maturity is relative to an industry-average TMF benchmark glide path.

2. **Average Beta to Target (ABT)**
   The average beta to target for a given year averages the YTT betas from that given year to
the TMF target maturity year. This measure is an aggregate forward-looking relative risk measure at every year to maturity for a TMF glide path relative to the TMF industry average glide path.

3. TMF Mean Absolute Deviation (MAD)
The TMF mean absolute deviation is an estimate of a TMF family’s average annual portfolio change over its entire glide path. A TMF's MAD is measured by first calculating the annualized rolling window style analysis (RWSA) and then measuring the annual style changes. This statistic provides a diagnostic tool to distinguish between market timing ability and excess trading that increases transaction costs.

4. Active Market Timing Performance
The market timing ability of the TMF family manager is estimated using the excess returns of the manager from following the RWSA asset allocation minus the returns from following the GPSA totally passive TMF custom benchmark glide path for the manager's family.

5. Active Selection Performance
The investment selection performance of the TMF family manager is estimated from the excess returns of the manager over the returns from RWSA asset allocation.

6. Investor Wealth Ratio at Target Date
It is important to evaluate the possible investor outcomes at target date from following a particular investment strategy. The investor wealth ratio at target date is a statistic provided for a representative participant, which is calculated using a TMF Monte Carlo forecaster such as YourOutcome.com. For a representative investor, this application provides the ratios of one’s projected wealth distribution at the target date that results from investing in a particular TMF family or from investing monies in the TMF industry average.

In order to explain the GPSA solution we detail the analytical methods underlying GPSA, validate that GPSA works to recover synthetically constructed glide paths created from synthetic returns and detail GPSA results for three leading TMF families. As such, this paper is sequenced as follows:

- Returns-Based Style Analysis Overview
- Rolling Window Style Analysis
- Glide Path Style Analysis Benchmark
- Validating GPSA Benchmarks
- GPSA of Actual TMF Funds
- TMF Industry Average Benchmark
- TMF Performance Metrics
- TMF Information from the Statistics
- TMF Wealth and Outcome Forecasting

Returns-Based Style Analysis Overview
Returns-based style analysis has been widely adopted in the investment management industry as a tool to assess the performance of managers. RBSA relies on a number of strong assumptions, and understanding how those assumptions are violated is the key to interpreting results and deriving new insights.

RBSA is a statistical optimization technique that solves for a portfolio of selected indexes that most closely mimic the behavior of an investment vehicle over a specified period of time. The advantage of RBSA over linear regression is that short-sale portfolio constraints can be specified in RBSA. Nobel Laureate in Economics W. F. Sharpe recommends using a palette of asset class indexes that are mutually exclusive and exhaustive. Accordingly, for this paper we use an asset palette consisting of cash, U.S. aggregate bonds, U.S. large cap stocks, U.S. small/mid cap stocks, and international stocks indices. The R-squared statistic reflects how well the RBSA model explains the behavior of the investment’s historical performance.

RBSA assumes that the style and skill of the manager are uncorrelated and that style is constant through time. Accordingly, RBSA results can be interpreted as average style weights over the sample period. Thus, traditional RBSA cannot be used for analysis of investments such as TMFs, which change their asset allocation over time.
Rolling Window Style Analysis Overview

Sharpe suggests using a “rolling window” to check for shift in style over time, that is, rolling window style analysis. RWSA is implemented by repeatedly performing RBSA on a subset of the returns data that moves along with observed history. If RBSA is performed on a small window, the resultant style analysis provides an estimate of asset allocation around the midpoint time of the window used. This insight is crucial to the breakthrough GPSA method.

In practice, what limits the use of small windows for RBSA is that measurement noise in returns distorts the optimization results; it is especially bad in small samples. We will address this limitation in the next section.

For example, we use a 12-month window to analyze the historical behavior of the fund members of TMF family A and display sample results in chart 1. As expected, the funds changed their asset allocation over time, but there is also significant amount of statistical noise. As can be seen from the RWSA results of TMF family A 2040 fund, the results indicate that the fund has around a 96% allocation to stocks in 2002 and that allocation seems to shift slightly toward bonds after 2003. While the TMF family A 2010 fund shows a much more significant and growing exposure to bonds.

Glide Path Style Analysis Overview

GPSA transforms these rolling window results into a common time-based measure by subtracting the midpoint of the RBSA window from the target date of the fund. Thus, the center of each time window provides an estimate of the fund manager allocation based on length of time from target date. This common unit allows GPSA to consolidate all the RWSA for all the target date funds from a particular family. The aggregate results for TMF family A in chart 2 provide new clarity to the funds’ behavior. From this, it is apparent that their style exposure behavior becomes more conservative as they approach their target dates. In addition, for this particular fund family, the glide path allocations continue to become more conservative even after fund maturity dates.

To address the RWSA measurement noise, the GPSA method fits a generalized logistic multivariate function family that represents asset class portfolio transition over the style asset allocation over time. In performing this functional fit, GPSA makes assumptions that the TMF asset allocation decisions are deterministic simply based on time from maturity date and are consistent across all funds within a particular TMF family. The GPSA method solves for the model parameters that make each glide path’s annual asset allocation glide point model returns as close as possible to the historical returns of the style asset allocation of the TMF family. The GPSA method covers and allows for both linear and nonlinear mathematic function families, as well as single and piecewise fits for different time horizons.
Validating Glide Path Style Analysis

To test the validity of GPSA methodology, we constructed idealized target maturity funds and then used the GPSA analytics to recover the idealized TMF glide paths. The goal is to create some idealized TMF families that resemble actual industry reference points and see how well GPSA performs in recovering them. In the tests that follow, the GPSA analytics recovered glide paths that account for more than 99.9% of the variance of the idealized TMFs. Although such precision cannot be possible in the real world because of market frictions, it demonstrates that the GPSA method derives applicable results.

We created idealized TMF funds that model three well-known TMF families to obtain GPSA benchmark results. TMF family A is one of the TMF industry pioneers. TMF family B actively manages its own funds, and TMF family C passively tracks a set of third-party TMF target year indices.

To construct the idealized TMFs, we used publicly available information to enable our results to be easily verified. Accordingly, we obtained information about the published target maturity fund glide paths from the TMF providers’ Web sites. From the TMF family A Web site we obtained a detailed year-by-year asset allocation for its target maturity funds and mapped its published assets classes into our sample 5 asset class palette. For TMF families B and C, we found that only their stock/bond split information was available. We used their published asset allocation every 5 years and linearly interpolated between them making stylized assumptions to map into our sample 5 asset class palette at every month to maturity. For family B we assumed that large mid-cap and international equity had approximately equal percentage allocations. For TMF family C we assumed zero allocation to international equities. Using this data, we constructed idealized 5-year synthetic monthly returns histories for each test family for idealistic target maturity funds with target dates 2010, 2020, 2030, and 2040.

Chart 3a shows the RWSA and the GPSA of our idealized version of TMF family A. As can be seen, GPSA recovers the key characteristics of the style of the family, including the small cash position and the long-term bond position and explains more than 99.9% of the behavior of this test family.

Chart 3b shows the RWSA and the GPSA of our idealized version of TMF family B. As can be seen, the GPSA method using RWSA recovers that the family supports 100% equity exposure after 30 years and has about equal allocation to U.S. mid/small cap and international stocks. GPSA explains more than 99.9% of the behavior of this test family.
Chart 3c shows the RWSA and the GPSA of our idealized version of TMF family C. As can be seen, the GPSA method using RWSA recovers that the family has no allocation to international stocks and obtains the correct stock/bond split as well as the subsplits between cash and bonds. GPSA explains more than 99.99% of the behavior of this test family.

Chart 4a shows the GPSA of TMF family A. The first plot shows the results of the 12-month rolling window RBSA, and the second plot shows the results of the GPSA model. Family A contains a target date 2000 fund; thus, it has asset allocations for 7 years past its original maturity date. We can see that this fund family’s asset allocation continues to become more conservative after maturity. The GPSA model explains about 96% of the variance of the entire family’s historical returns. When we compare the actual GPSA results to the idealized TMF family A results from chart 3a, we can see that in terms of stock/bond allocation, the actual funds behaved more conservatively during and after maturity date than is published by the TMF family. In addition, the GPSA indicates the actual funds behave more aggressively than published at 40 years to retirement.

Chart 4b: TMF Family C Consolidated Rolling SA and GPSA Model.

Chart 3c: Idealized TMF Family C, Comparison of Original and Fitted Glide Paths.

These results of GPSA for our idealized TMF family glide paths demonstrate that the method can accurately infer the glide path investment strategies based on the observed returns behavior of the fund families. Thus, this technique enables us to extend the power of RBSA to the previously opaque world of TMFs.

**GPSA Application to Actual Funds**

We next applied GPSA to the three TMF families’ actual historical institutional returns and compared the results with our synthetic TMFs.

Chart 4a: TMF Family A Consolidated Rolling SA and GPSA Model.

In the TMF family B results from chart 4b, we can see the actual funds behave as if they have a higher bond allocation compared to TMF family B’s published glide path strategy (in chart 3b). This indicates that TMF family B managers are behaving more conservatively than the idealized version of their strategy. Because this family is actively managed, the managers could be trying to time the market while the economy is heading into a recessionary environment. However, this also implies that when the economy recovers, the TMF family B managers could revert to a more aggressive stocks allocation than published.
Chart 4c shows the GPSA of TMF family C that attempts to track a set of published third-party target date indices. Accordingly, we expect GPSA to be able to fit this rather well. As can be seen, and confirming our expectations, the GPSA model explains 98% of the variance of the TMF family’s historical returns.

When we compare the actual GPSA TMF family C glide path to the idealized TMF family C fund glide path (in chart 3c), we can see that the actual funds’ GPSA glide path matches well, though there is some significant high-frequency noise around the glide path. The GPSA glide path when compared to the idealized glide path shows a marginally higher stock allocation and a larger allocation of the fixed income allocation to cash than we assumed in our idealized model. Furthermore, the GPSA shows lower U.S. small/mid cap stocks allocation compared to the presumed idealized glide path strategy. When we constructed the idealized glide path, we had assumed TMF family allocated equity to U.S. stocks only, and there is clearly an international equity allocation needed to explain the variance of returns.

**TMF Industry Average Glide Path**

We next performed GPSA on all TMF fund families with publicly available institutional share class returns data and calculated the equally weighted TMF industry average benchmark glide path. We display the results in chart 5. With the use of the GPSA methodology, the industry average glide path can be projected onto any asset class palette, including ones with more granular asset classes than the basic five used.

This GPSA TMF industry average glide path then serves as an appropriate market-based benchmark for all other target maturity glide paths. The GPSA TMF industry average glide path reflects the collective methodology wisdom and investment management experience of the entire set of public target maturity investment providers. One important metric this benchmark allows us to calculate now is the relative riskiness of a particular TMF family glide path relative to the GPSA TMF industry average glide path.

**Alternative Industry Benchmarks**

The average beta to target can be used to cluster all TMF families’ glide paths into two sets: the aggressive (higher ABTs) and the conservative (lower ABTs) at 50 years from retirement. These averages of the two sets are calculated and displayed in chart 6.
**TMF Relative Risk Measures**

As we noted earlier, the traditional concept of beta cannot be used for TMFs. Using GPSA we obtain a new measure called years to target beta, which measures, at point in time and at any particular year the relative risk of the particular TMF glide path asset allocation to the TMF industry average benchmark glide path asset allocation. TMF family A starts out about the same risk as the industry average TMF at 50 years to target. However, the family does not glide down its risk as fast as the TMF industry average asset allocation. Accordingly, its relative YTT beta continues to climb to 1.05 at 15 years to target date. Then family A rapidly dials down its risk, and with 5 years to target the YTT beta crosses 1.0. At the target date the family's beta is only 0.92.

![Graph](image)

**Chart 7: TMF Family A Beta by Years to Target and Average Beta to Target.**

For any particular investor, a highly relevant evaluation metric for a target maturity investment is the relative aggregate risk that the investor faces from now until his or her target date. Thus it is important to create a risk measure that reflects the forward-looking aggregate risk component. The ABT at every year along the glide path is calculated by averaging the YTT betas from that year to each fund's target maturity year. As can be seen in chart 7, the ABT for TMF family A for 50 years to retirement is about 1.02. Thus, it is more risky in aggregate over the entire glide path than the GPSA TMF industry average glide path for a younger investor. On the other hand, at 12 years to retirement, its ABT is 1; thus, it is on average just as risky as the industry average TMF benchmark. Later the fund family behaves more conservatively than the industry average.

<table>
<thead>
<tr>
<th>TMF Family</th>
<th>2010</th>
<th>2015</th>
<th>2020</th>
<th>2030</th>
<th>2040</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>92%</td>
<td>95%</td>
<td>99%</td>
<td>102%</td>
<td>103%</td>
</tr>
<tr>
<td>B</td>
<td>92%</td>
<td>92%</td>
<td>93%</td>
<td>95%</td>
<td>96%</td>
</tr>
<tr>
<td>C</td>
<td>79%</td>
<td>80%</td>
<td>80%</td>
<td>82%</td>
<td>84%</td>
</tr>
</tbody>
</table>

Table 1: Average Beta to Target by Target Maturity Years

Table 1 shows the ABT for each fund family’s TMFs and highlights that they have significant differences in their relative risk. The table shows that TMF family A is riskier than the GPSA TMF industry average benchmark for an investor in the 2040 fund. However, for an investor in the 2015 fund, TMF family A’s risk becomes more conservative than the industry average. The table also shows that TMF family B is more conservative than the TMF industry average benchmark and family A for all target years. Last, TMF family C is the most conservative of all for all years to target.

**TMF Relative Performance Measures**

The GPSA passive benchmarks provide us with a robust base to benchmark any TMF manager's performance. GPSA allows the calculation of each manager’s market timing returns, selection returns, and the total alpha returns for each of the fund families. These results are based on the established industry practice of RBSA.

**TMF Portfolio Mean Absolute Deviation**

TMF MADs of the style weights calculated from RWISA provide a statistical measure of year-to-year portfolio style consistency. We calculate the MADs for the RWISA annual style weights of each fund in each family and then time weight these values based on the length of returns history of each fund. The average of the family’s fund MADs is the absolute annual deviation per year of the portfolio style weights. Higher values of TMF MADs indicate active management and result in correspondingly lower values for GPSA R-squared statistics.
Active Market Timing Returns
The market timing returns is a measure of the ability of a manager to actively time the market movement while trying to follow a deterministic glide path. It is evident from charts 4a–c that the RWSA is rather noisy. However, these shifts in asset allocation around the passive glide path could be the deliberate results of market timing by the fund manager. GPSA calculates the market timing returns as the arithmetic difference between the returns from following the asset allocation obtained from the RWSA and the returns from following a deterministic GPSA model:

\[ r_{\text{Market Timing}} = r_{\text{RollingWindowSA}} - r_{\text{GPSA}} \]

A mean positive average value for the market timing returns indicates that in the sample the manager is on average able to add value through timing the market. Market timing is easy to detect because it is generally accompanied by a high asset turnover ratio within a mutual fund.

Active Investment Selection Return
Active investment selection returns is a measure of how much the manager is able to beat his or her rolling window style benchmark. It is calculated as the arithmetic difference between the TMF’s historical returns and the returns of its RWSA:

\[ r_{\text{Selection}} = r_{\text{History}} - r_{\text{RollingWindowSA}} \]

A positive average value of selection returns indicates that in the returns sample the manager is on average able to add value through factors unexplained by the asset classes used in the analysis. Generally, the higher the expense ratio of a mutual fund, the lower its active investment selection returns.

Total Excess Returns
The total excess returns is the sum of the market timing and selection returns and is directly calculated as the arithmetic difference between the TMF’s returns and the returns of the GPSA asset allocation:

\[ r_{\text{Excess}} = r_{\text{History}} - r_{\text{GPSA}} = r_{\text{Market Timing}} - r_{\text{Selection}} \]

Information from GPSA Statistics
We used all available monthly historical returns through March 2008 as the sample period for the following section.

We can see from table 2 that, in the sample period, TMF family A demonstrates no market timing ability above the passive GPSA investment strategy.

<table>
<thead>
<tr>
<th>TMF Family</th>
<th>Adj. R-Sq</th>
<th>Mean Absolute Deviation</th>
<th>Market Timing Return</th>
<th>Investment Selection Return</th>
<th>Total Excess Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>96%</td>
<td>39%</td>
<td>0.0%</td>
<td>-0.2%</td>
<td>-0.2%</td>
</tr>
<tr>
<td>B</td>
<td>95%</td>
<td>60%</td>
<td>0.0%</td>
<td>-0.3%</td>
<td>-0.3%</td>
</tr>
<tr>
<td>C</td>
<td>98%</td>
<td>30%</td>
<td>-0.2%</td>
<td>-0.6%</td>
<td>-0.8%</td>
</tr>
</tbody>
</table>

Table 2: Active Performance Measures

On the other hand, TMF family C has the smallest TMF MAD and a very high R-squared value and yet significantly underperforms in market timing. Furthermore, TMF family C also has the worst investment selection and total excess returns in this sample of TMF families.

<table>
<thead>
<tr>
<th>TMF Family</th>
<th>Turnover Ratio</th>
<th>Expense Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>11%</td>
<td>0.35%</td>
</tr>
<tr>
<td>B</td>
<td>43%</td>
<td>0.36%</td>
</tr>
<tr>
<td>C</td>
<td>126%</td>
<td>0.83%</td>
</tr>
</tbody>
</table>

Table 3: Annual Turnover Ratio and Expense Ratio of TMF Families

Table 3 shows the expense ratio and annual portfolio turnover for these three TMF families. The displayed turnover ratios and expense ratios for the fund families are calculated as the capital weighted average of the ratios of all target date funds in all share classes of each family.

TMF family A has the lowest annual turnover and the lowest average expense ratio among the three families. The characteristics and actions of this family are consistent with having a minimally active philosophy. The family incurs a higher tracking error relative to its GPSA glide path and has a higher portfolio MAD than that of TMF family C presumably because family A waits to make the minimal prudent adjustments needed to rebalance its portfolios. It has a low expense ratio and makes as few transactions as possible. Yet,
TMF family A took a decisively active management stance in the current recessionary environment and added a bond allocation to its very-long-term equities-only portfolios, thus reducing its losses in the declining equities markets.

In the sample, TMF family B is just slightly below TMF family A in terms of overall active performance and has about the same average expense ratio. TMF family B’s higher tracking error, higher portfolio MAD, and much higher turnover ratio indicate that the family employs a much more active strategy than that of family A. For its active effort, family B did not manage to earn positive market timing returns. In addition, despite its low expense ratio, the family has a slightly higher negative historical selection return than family A. This could be due to the higher transaction costs from increased turnover.

TMF family C is the most interesting case. It has the highest expense ratio and annual portfolio turnover among the three families. This would typically indicate that TMF family C is actively managed. The paradox is that TMF family C also has a stated passive focus to track an external proprietary TMF index benchmark. This is confirmed by the low tracking error (the high R-squared) and low annual portfolio MAD, both of which are associated with passively managed funds.

These two pieces of evidence may seem contradictory at first. However, TMF family C’s goal could be to minimize the tracking error to its benchmark, and this goal appears to be achieved by excessively high frequency rebalancing of its portfolios that resulted in market timing losses in the recently declining equities market. The high transaction costs combined with high expense ratio further reduced TMF family C’s selection returns during the sample period.

The GPSA method provides unparalleled powerful diagnostic tools, and the previous measures demonstrate how it allows us to uncover insights into the passive and active performance of TMF fund families.

**TMF Absolute Performance Measures**

In evaluating TMFs one needs to understand the annual expected return and risk of the investment strategy as well as the probable resulting investor wealth outcomes at target date. These performance measures require further assumptions about the expected returns, risks, and correlations of the underlying returns of the asset classes.

To create these estimates we have to make some assumptions. We are interested in real returns because we want to project into the future in today’s dollars. First, we transform the historical returns to excess returns net of expected inflation. We calculate a pair-wise longest history of excess returns correlation matrix. The risk is calculated separately for each asset class. We calibrate a coefficient of relative risk aversion of 6.5 for a Capital Asset Pricing Model (CAPM) model to fit the expected returns to the historical averages. There is academic consensus that the forward risk premium could be smaller than the historical value. Accordingly, we reduce the CAPM relative risk aversion to 6, which reduces the expected average real returns for each asset class by 2.2%. The model expected returns are blended with historical returns using a Black-Litterman Meucci framework with a 50% confidence weighting, which results in average expected real return being reduced by 1.4%. The appendix displays the resulting expected real returns and standard deviations used.

**TMF Family Expected Risk and Real Returns**

The expected returns and covariance of asset classes are then combined with each TMF family’s GPSA asset allocation glide path to calculate the expected real return and risk for each year from the target date. Chart 8 shows the 2008 expected returns and risks for our three sample TMF families for peer groups 2010, 2020, 2030, 2040, and 2050. As can be seen, the passive glide path risk of family A is higher than B, which is higher than C for all target dates.
Investor Wealth Ratio at Target Date

It is crucial to evaluate realistic potential investor outcomes at the target date achieved by following a particular investment strategy. An important evaluation criterion for a target maturity investment strategy is to compare the resulting distribution of wealth at the target date versus the distribution of wealth generated by following a benchmark investment strategy, such as the GPSA TMF industry average benchmark.

The resulting distribution not only depends on time but also on the weightings of contribution cash flows made every year until the target year. Producing such a result requires a number of additional assumptions about the capital markets and requires investor-specific information about initial wealth and contribution cash flows. A glide path–aware Monte Carlo simulation can be used to project the retirement wealth. The investor wealth ratio at target date is a statistic provided for a representative investor that can be calculated using a TMF Monte Carlo forecaster such as YourOutcome.com. To compile the results for table 4, we assume a sample investor is 35 years old, has $50,000 starting wealth, earns $65,000 per year before taxes, and saves 5% annually on a pretax basis.

Table 4 shows the sample investor results with a ratio of the projected wealth at the target date from investing in a particular TMF family versus investing in the industry average TMF. The wealth ratio at target date is calculated at multiple percentiles of the distribution of wealth at target date. A more in-depth study of such forecasts will be the basis of the forthcoming paper titled “Retirement Savings and Income Guidelines using Target Maturity Funds.”

<table>
<thead>
<tr>
<th>Ending Wealth at Target Date</th>
<th>Family A</th>
<th>Family B</th>
<th>Family C</th>
<th>Max-Min Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>20%</td>
<td>$341,217</td>
<td>$344,929</td>
<td>$335,668</td>
<td>$311,997</td>
</tr>
<tr>
<td>50%</td>
<td>$500,866</td>
<td>$505,500</td>
<td>$485,177</td>
<td>$430,228</td>
</tr>
<tr>
<td>80%</td>
<td>$766,583</td>
<td>$777,213</td>
<td>$733,845</td>
<td>$629,885</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ending Wealth % of GPSA Industry Average Results</th>
<th>20%</th>
<th>50%</th>
<th>80%</th>
</tr>
</thead>
<tbody>
<tr>
<td>101.09%</td>
<td>98.37%</td>
<td>91.44%</td>
<td>9.65%</td>
</tr>
<tr>
<td>100.93%</td>
<td>96.87%</td>
<td>85.90%</td>
<td>15.03%</td>
</tr>
<tr>
<td>101.39%</td>
<td>95.73%</td>
<td>82.17%</td>
<td>19.22%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Synthetic Annuity Annual Retirement Income Estimates</th>
<th>20%</th>
<th>50%</th>
<th>80%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$21,611</td>
<td>$21,844</td>
<td>$21,263</td>
<td>$19,777</td>
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<tr>
<td>$31,634</td>
<td>$31,925</td>
<td>$30,649</td>
<td>$27,199</td>
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<tr>
<td>$48,317</td>
<td>$48,984</td>
<td>$46,261</td>
<td>$39,735</td>
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Table 4: Forecast Results from www.YourOutcome.com

Summary

Business Logic’s patent-pending GPSA method and benchmark solutions bring new transparency to the previously opaque world of target maturity funds. Using GPSA, interested parties not only can answer questions about target maturity investments risk and return characteristics but also obtain benchmarks to evaluate TMF fund managers in terms of their risk and performance compared with their family-specific marketed asset allocation strategies and with the GPSA TMF market-based benchmarks.

The equally weighted GPSA TMF industry average glide paths and statistics created through the GPSA process deliver the natural standards for market-based benchmark indexes for the TMF industry. For further information on using Business Logic’s GPSA target maturity analytics and data products, please contact Business Logic at www.businesslogic.com or 312-264-7000.
References

1. YourOutcome.com provides glide path Monte Carlo forecasts of TMF investments based on investor profile specific information.


Appendix: Capital Market Assumptions

<table>
<thead>
<tr>
<th>Exp Real Return</th>
<th>Risk</th>
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</thead>
<tbody>
<tr>
<td>Inflation</td>
<td>2.8%</td>
</tr>
<tr>
<td>Cash</td>
<td>1.1%</td>
</tr>
<tr>
<td>US Bonds</td>
<td>2.4%</td>
</tr>
<tr>
<td>US Large Cap Stocks</td>
<td>7.0%</td>
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<tr>
<td>US Mid/Small Cap Stocks</td>
<td>8.4%</td>
</tr>
<tr>
<td>International Equity</td>
<td>7.1%</td>
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</tbody>
</table>

Table 5: Annualized Real Expected Return and Risk Assumptions

About the Author

Navaid Abidi completed a BS in Electrical Engineering at the Milwaukee School of Engineering and graduated Summa Cum Laude with an MBA in Analytic Finance and Econometrics from the University of Chicago GSB. Prior to his current role at Business Logic, Mr. Abidi spent 11 years in the financial services industry, 8 years as a technologist and architect and 3 years leading a global statistical arbitrage quantitative trading group for a hedge fund.

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440 North Wells Avenue
Chicago, IL 60610 USA
http://www.businesslogic.com
312-264-7000

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