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## Original Article

# The efficiency of target-date funds

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**ABSTRACT** To evaluate the efficiency of target-date funds (TDFs), one of the fastest growing lines of mutual funds, we take 36 TDF series offered in the market and calculate investors' welfare loss from TDF investment. We divide welfare loss into two categories: loss from suboptimal risky portfolio and loss from inappropriate glide path. We find that inappropriate glide path constitutes the major source of TDF performance inefficiency. This inefficiency could reduce an investor's annual consumption by up to 17 per cent. We also find that the substantial heterogeneity in TDF performance is primarily caused by variation in glide paths. The heterogeneity contradicts the notion that one TDF fits everyone and it confirms the urgency to match TDF selection to investors' risk profiles. In this spirit, we advocate a *risk-based selection strategy* as a remedy for TDF inefficiency. We estimate that this strategy could reduce approximately half of the welfare loss suffered from other commonly used strategies.

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**Keywords:** target-date funds; life-cycle model; retirement saving; mutual fund performance; dynamic optimization model

## INTRODUCTION

Target-date funds (TDFs) are mutual funds that invest in a mix of assets and gradually adjust the portfolio to a more conservative allocation as the investor approaches a target retirement date. TDFs have surged in prominence in the past decade. Morningstar (2013) estimates that TDFs have collected US \$508 billion in the first quarter of 2013, compared with \$69.4 billion in 2002. This growth is particularly pronounced after

Department of Labor designated TDF as one of the three Qualified Default Investment Options under the Pension Protection Act of 2006, aiming at rectifying the documented portfolio errors that hinder efficient 401(k) investment decisions. The act has pushed TDFs as by far the most popular default investment option in defined contribution (DC) plans (U.S. Government Accountability Office, 2011). In 2011, 13 per cent of total 401(k) assets and 31 per cent of the account

balances of recently hired participants in their twenties were invested in TDFs. The prevalence of TDFs makes their performance critical to retirement income of over 88 million American private sector workers (Mitchell and Utkus, 2012; U.S. Dept. of Labor, 2012; VanDerhei *et al*, 2012).

Notwithstanding their being designed as age-appropriate portfolios to help investors achieve retirement goals, some TDFs incurred substantial loss in the recent financial turmoil (Yoon, 2010). In fact, studies reveal considerable cross-sectional dispersions in TDF security selection, asset management strategy and risk roll-down schedule (glide path), and hence their dispersions in performance and risk exposure (Balduzzi and Reuter, 2012). As such, many argue that a single TDF is not appropriate for everyone. Nevertheless, this notion has received little further elaboration. There is a lack of empirical scrutiny to provide benchmarking guidance, or to identify the source of inefficiency. The need for empirical understanding and managerial guidelines on TDFs further escalates given TDFs' soaring popularity and ordinary investors' limited knowledge about them. Thus, this article aims to assess the efficiency of existing TDFs, to identify the source of inefficiency and to propose a remedy for TDF inefficiency.

TDF differs from the traditional mutual funds in that it not only provides *static* portfolio management to maximize mean-variance efficiency of the fund, it also promises to monitor the portfolio *dynamically* over time to make sure the asset allocation strategy (glide path) of the fund matches the investor's profile. Yoon (2010) pointed out that at the core of designing the TDFs is the glide path. Hence, the conventional mutual fund performance measures mainly focusing on risk-adjusted returns are not appropriate for TDFs, because they do not assess the appropriateness of TDFs' glide paths. Instead, the life-cycle optimization model that incorporates both investor labor income risk and risk preference serves as the theoretical

rationale for TDF investment philosophy (Schroder, 2013). Specifically, under life-cycle optimization models, an individual chooses how much to consume and how to allocate investment between risky and riskless assets over lifetime. The model asserts that lifetime utility can be maximized by using an asset allocation strategy (glide path) that tilts toward riskless assets as the individual approaches retirement, because the value of bond-like human capital decreases over time. In other words, the finding emphasizes the importance of an age-dependent glide path and it confirms the conventional wisdom that an investor's exposure to risky assets should decrease over time (see, for example, Bodie *et al*, 1992; Jagannathan and Kocherlakota, 1996; Cocco *et al*, 2005; Viceira, 2008).

In spite of the pioneering academic work in life-cycle investment in the past two decades, assessment of TDFs' glide paths has received little attention from practitioners. Financial management professionals routinely assess TDFs with antiquated tools. Industry reports and most practitioner research still evaluate TDFs with the static mean-variance model of efficient portfolio diversification (for example, Morningstar, 2013; Israelsen and Nagengast, 2012). The static mean-variance model evaluates only the security selection and management performance of a fund; it does not assess the fitness of the TDF glide path to an investor. Bridges *et al* (2010), Pang and Warshawsky (2011) and Poterba *et al* (2009a, b) intended to study the impact of glide paths on TDF performance. They simulated the long-term performance of different allocation strategies based on historical return distribution. However, their evaluation is restrictive because their models excluded labor income risk and multi-period consumption decisions, the key elements of age-dependent asset allocation model. Bodie (2003) stated that a person's welfare depends not only on his end-of-period wealth but also on the consumption of goods and leisure over his entire life; the

value, riskiness and flexibility of person's labor earnings are of first-order importance in optimal portfolio selection at each stage of the life cycle. The important role played by labor income risk on investor portfolio allocation decisions is further confirmed by Cardak and Wilkins (2009) using empirical data.

On the other hand, academic studies like Bodie and Treussard (2007), Cocco *et al* (2005) and Gomes *et al* (2008) adopted the latest academic finding on time-varying portfolio allocation in evaluating TDF performance. They used a realistically calibrated life-cycle model that incorporates labor income risk and individual risk preferences. In addition, they also considered investors' multi-period consumption and TDFs' asset allocation decisions. However, contrary to the practitioner work, those academic works neglected security selection (risky portfolio management) decision of TDF and focused only on the efficiency of asset allocation (glide path) even though the modern portfolio theory asserts that both 'security selection' and 'asset allocation' decisions are crucial to investment performance.

This article narrows the gap between practitioners and academics by considering both risky portfolio management and glide path design in TDF assessment. We adopt a realistically and quantitatively calibrated life-cycle model by Cocco *et al* (2005) with non-tradable labor income over time. The model allows us to dynamically construct an investor's optimal consumption and asset allocation decisions. We then compare investors' welfare under the optimal decisions versus the welfare using TDFs' actual return-risk statistics and glide paths. Thus, our study sets apart from previous work by using the actual TDF data instead of hypothetical or aggregate ones as in other studies (for example, Cocco *et al*, 2005; Bodie and Treussard, 2007; Gomes *et al*, 2008). Another distinction of our work is the ability to quantify and distinguish inefficiency because

of suboptimal risky portfolio versus inefficiency because of inappropriate glide path.

Our analysis has several important findings. First, we show that welfare loss is modest if investors select the optimal TDF among current market offerings; however, investors may lose much more in real life when they fail to take the appropriate TDFs that match their profiles. Second, we find that inappropriate glide path constitutes the major source of TDF inefficiency, accounting for 67.54 per cent of total welfare loss on average. This inefficiency could reduce an investor's consumption level by up to 17.12 per cent every year. On the other hand, suboptimal risky portfolio only accounts for less than a third of inefficiency. This result carries an important implication: much of the practical attention is misallocated to improve risky portfolio performance that has a relatively small impact on TDF efficiency. Inappropriate glide paths, on the other hand, hold a lion's share of inefficiency. Thus, investors could benefit more from better glide path design.

In addition, we observe significant heterogeneity in TDF performance: an investor's welfare varies substantially with different choices of TDFs. We attribute this heterogeneity primarily to variation in TDFs' glide paths. Such heterogeneity contradicts the idea that one TDF fits everyone. Hence, it is critical to select a TDF that matches an investor's risk preference, given that employees in DC plans are commonly offered funds from one single TDF provider. In light of this, we advocate a *risk-based selection strategy*, which focuses on matching the risk level of TDF with an investor's risk preference, as a solution to TDF inefficiency. While a fully customized fund for each investor would be an ideal option, it is extremely unlikely to implement such an expensive strategy. A *risk-based selection strategy* is a better balance between theoretical ideal and practical barriers. We compare the performance of this strategy with a *random*

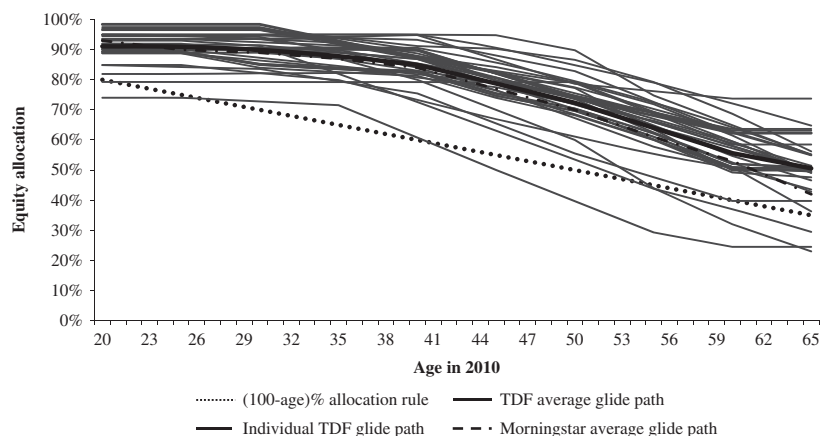
*selection strategy*, in which TDF is randomly chosen, and a *return-based selection strategy*, in which one chooses TDF with the highest past return. We find that the *risk-based selection strategy* reduces half of the welfare loss from the other two alternative strategies on average.

## DATA

We collect data from Securities and Exchange Commission’s (SEC) filing in the third quarter of 2010, which lists each TDF’s asset holdings and the allocated amount. We merge this data with the CRSP database to obtain the historical return of each of the TDF’s individual equity assets since 1997/1. To this, we add other TDF characteristics, such as the 2010 total return and fund expenses from Morningstar. The resulting data set contains information on 277 TDFs with target retirement dates ranging from 2000 to 2055. These 277 funds belong to 36 TDF series – a TDF series being a group of TDFs provided by the same TDF family but with various target dates. For example, ‘T. Rowe Price Retirement Fund’ is a TDF series, which is composed of 10 TDFs with various target retirement dates ranging from 2010 to 2055 with 5-year interval (for example, ‘T. Rowe Price Retirement 2010 Fund’ with target retirement year in 2010;

‘T. Rowe Price Retirement 2055 Fund’ with target retirement year in 2055).

We derive the implied glide path of each TDF series using funds within that series with target retirement years ranging from 2010 through 2055. This method is commonly used in prior studies to determine TDF glide path (see, for example, Poterba *et al*, 2009a; Pang and Warshawsky, 2011; Morningstar, 2013). Take the TDF series ‘T. Rowe Price Retirement Fund’, for example, in 2010, ‘T. Rowe Price Retirement 2010 Fund’ contains the portfolio designed for a 65-year-old investor while ‘T. Rowe Price Retirement 2015 Fund’ contains the portfolio for a 60-year-old investor, assuming everyone plans to retire at age 65. On the basis of these two funds’ compositions, we can easily conclude the risk exposures for investors at ages 65 and 60 in ‘T. Rowe Price Retirement Fund’ series. However, risk shares for investors between age 60 and 65 are missing because TDFs are offered at a 5-year interval. Hence, we interpolated asset allocations between age 60 and 65 assuming that TDF’s risk share decreases linearly over time. This method allows us to depict the full glide path for the 36 TDF series as shown in Figure 1. In summary, for each of the 36 TDF series, we obtained detailed information on its glide path, historical returns of underlying equity assets and other fund characteristics such as 2010 total return and expense ratios.



**Figure 1:** Glide paths of TDF offerings, (100-age) per cent allocation rule and Morningstar average.

**Table 1:** Summary statistics

	Our sample					Morningstar survey on entire market
	N	Mean	Standard deviation	Minimum	Maximum	
Total assets in 2010 (sum of all TDFs, in million \$)	277	256 859				341 000
Total returns in 2010 (%)	239	13.33	1.96	6.18	16.75	
Target date 2000–2010	32	10.61	1.51	6.18	13.44	10.68
Target date 2011–2015	29	11.49	1.30	8.75	14.01	11.50
Target date 2016–2020	24	12.54	1.20	10.69	14.74	12.27
Target date 2021–2025	27	13.36	1.05	11.55	15.37	13.29
Target date 2026–2030	24	13.88	1.10	11.42	16.15	13.47
Target date 2031–2035	26	14.45	1.08	12.45	16.34	14.28
Target date 2036–2040	24	14.68	1.24	11.70	16.51	14.37
Target date 2041–2045	25	14.92	1.08	12.23	16.49	14.60
Target date 2050+	28	14.87	1.34	12.06	16.75	14.45

Notes: This table shows the total assets held by all TDFs in our sample in 2010 and the total assets of all TDFs in the market reported by Morningstar survey. It also compares the total returns of sample TDFs with returns of TDFs in the market at various target dates. We use data from SEC’s filing in the third quarter of 2010 to calculate ‘total assets in 2010’ of sample TDFs. ‘Total returns in 2010’ are based on data from Morningstar. We use statistics from Morningstar (2011) industry survey to estimate TDF characteristics in the entire market.

Table 1 summarizes statistics of our TDF sample. To demonstrate the representativeness of our sample, we also show the statistics from the Morningstar survey on the entire TDF market in 2010. The 36 TDF series in our sample account for over 75 per cent of the \$341 billion TDF market in 2010 (Investment Company Institute, 2011; Morningstar, 2011). The returns of our sample series represent the overall TDF market performance.<sup>1</sup> For example, the 32 TDFs with target dates ranging from 2000 to 2010 in our sample have an average 2010 total return of 10.61 per cent, which closely matches the 10.68 per cent return in the Morningstar survey. In addition, Figure 1 depicts the average glide path of the 36 TDF series in our sample alongside the Morningstar survey average. Here, the glide path of our samples resembles the Morningstar average, confirming that our sample series represent the majority of the TDF market in 2010.

In addition, Figure 1 shows substantial dispersion in the glide paths, both in equity exposures at any given age and the timing and rate at which the funds shift from aggressive to conservative allocation. For example, at age 55 (the 2020 TDF offered in 2010) the most

aggressive fund has a 79 per cent equity allocation while the most conservative fund has a 29 per cent equity allocation – a difference of 50 per cent.

Figure 1 also depicts the glide paths of our sample funds alongside a (100–age) per cent allocation rule – a common heuristic that many practitioners use, which allocates (100–age) per cent of the asset to equity throughout lifetime (Bodie and Crane, 1997). This (100–age) per cent rule is also the hypothetical life-cycle allocation strategy commonly used in the literature to represent TDF glide path. Figure 1 shows that the (100–age) per cent rule is considerably lower than the actual TDF equity allocations. Consequently, using the (100–age) per cent rule to evaluate TDF efficiency may not reflect the actual performance of the current market offerings and the heterogeneity in their outcomes.

## METHODOLOGY

### Model

We adopt the model from Cocco *et al* (2005), which is a realistically calibrated life-cycle model with non-tradable labor income. This model is commonly used in the multi-period

life-cycle optimization literature (for example, Campbell *et al*, 2001; Horneff *et al*, 2010). We adopt the model to analyze an investor's optimal consumption and asset allocation decisions. In particular, let  $i$  be the index for an investor and  $t$  be the time. The investor will retire at time  $K$  and pass away for sure at time  $T (>K)$ . An investor's preference is represented by the following time-separable power utility function:

$$E_1 \sum_{t=1}^T \delta^{t-1} \prod_{j=0}^{t-1} p_j \frac{C_{i,t}^{1-\gamma}}{1-\gamma} \quad (1)$$

where  $\delta$  represents the discount rate,  $C_{i,t}$  is the consumption level at time  $t$ ,  $\gamma$  indicates the investor's risk preference and a higher  $\gamma$  represents a more risk-averse investor, and  $p_t$  denotes the probability that the investor is alive at time  $t+1$ , conditional on being alive at time  $t$ .  $(C_{i,t}^{1-\gamma})/(1-\gamma)$  captures the investor's utility from consumption  $C_{i,t}$ .

To measure the value of human capital, assume that investor's income at time  $t$ ,  $Y_{i,t}$ , before retirement time  $K$  is given by

$$\log(Y_{i,t}) = f(t, Z_{i,t}) + v_{i,t} + \varepsilon_{i,t} \quad (2)$$

for  $t \leq K$ .

The log income consists of a deterministic function and two random components.  $f(t, Z_{i,t})$  denotes the deterministic function of age and a vector of other individual characteristics  $Z_{i,t}$ .  $\varepsilon_{i,t}$  is an idiosyncratic temporary income shock following  $N(0, \sigma_\varepsilon^2)$ . The first-order autoregressive process  $v_{i,t}$  is given by

$$v_{i,t} = v_{i,t-1} + u_{i,t} \quad (3)$$

where the permanent income shock  $u_{i,t}$  follows  $N(0, \sigma_u^2)$ , and  $u_{i,t}$  is assumed to be uncorrelated with  $\varepsilon_{i,t}$ .

After retirement, an individual's income is modeled as a constant fraction of his permanent labor income during the last working year:

$$\log(Y_{i,t}) = \log(\lambda) + f(K, Z_{i,K}) + v_{i,K} \quad (4)$$

for  $t > K$ .

At each time  $t$ , the investor can invest in a risky asset and a riskless asset. The riskless asset has a constant gross real return  $\bar{R}_f$ . The excess return of the risky asset  $R_t$  follows:

$$R_t - \bar{R}_f = \mu + \eta_t, \quad \eta_t \stackrel{iid}{\sim} N(0, \sigma_\eta^2). \quad (5)$$

We assume that an investor invests  $\alpha_{i,t} \in [0, 1]$  proportion of his savings in the risky asset at time  $t$  and invests his remaining savings in the riskless asset. In this case, his return on the portfolio follows

$$R_{i,t+1}^p = \alpha_{i,t} R_{t+1} + (1 - \alpha_{i,t}) \bar{R}_f \quad (6)$$

Therefore, over a lifetime, the investor will accumulate wealth following

$$W_{i,t+1} = R_{i,t+1}^p (W_{i,t} + Y_{i,t} - C_{i,t}). \quad (7)$$

The investor needs to choose the optimal consumption and asset allocation path  $\{C_{i,t}^*, \alpha_{i,t}^*\}_{t=1}^T$  to maximize equation (1) subject to (2)–(7) and borrowing and short-sales constraints. Finally, the welfare is measured by a constant consumption stream  $\{\bar{C}\}_{t=1}^T$  that makes the investor equivalently well-off in expected utility as the consumption stream financed by the investment strategy under analysis (Cocco *et al*, 2005). Specifically,

$$\bar{C} = \left[ \frac{(1-\gamma)V}{\sum_{t=1}^T \delta^{t-1} \left( \prod_{j=0}^{t-1} p_j \right)} \right]^{\frac{1}{1-\gamma}} \quad (8)$$

where  $V = E_1 \sum_{t=1}^T \delta^{t-1} \prod_{j=0}^{t-1} p_j (C_{i,t}^{*1-\gamma}) / (1-\gamma)$  shows the expected utility the investor derives from the optimal consumption stream  $\{C_{i,t}^*\}_{t=1}^T$ . Every asset allocation strategy generates a different consumption path. Thus,  $\bar{C}$  enables a uniform measure to compare performances across different strategies.

The problem is analytically intractable, so we solve it numerically using backward induction. We discretize state space and derive the optimal decisions using Nelder-Mead grid search, and we approximate the expected utility of any given decision using Gauss-Hermite quadrature. Details on

numerical solution techniques are provided in Appendix A.

## Calibration

We follow the standard calibration set-up in the literature. Investors start to work at age 20 (22 for college graduates), retire at age 65 and die with certainty at age 100. We set the discount factor  $\delta$  to 0.96. To calibrate the labor income process (2)–(4), we adopt the wage profiles for non-high school, high school and college graduates reported in Cocco *et al* (2005) and Gomes *et al* (2008) with transitory labor income shock  $\sigma_\varepsilon$  at 13.89 per cent and permanent shock  $\sigma_u$  at 10.95 per cent. The return and risk inputs for risky assets vary in distinct scenarios and will be discussed in detail in later sections. We use the average annual T-bill rates during 1997/1 and 2010/7 as riskless return, which yields a 3.07 per cent annual return. We consider three risk preference parameters  $\gamma = 2, 5$  and 8. We also derive the earning paths for investors with no-high school, high school and college education backgrounds, respectively. In this way, we create nine investor profiles ( $i = 1 \dots 9$ ), each representing a combination of risk preference and education level.

## TDF efficiency measures

In the following three steps, we measure TDF efficiency.

*Step 1 – Optimal solution:* We numerically solve a dynamic optimization model to derive the optimal consumption decision and asset allocation path  $\{C_{i,t}^*, \alpha_{i,t}^*\}_{t=1}^T$  that maximize equation (1) subject to (2)–(7). In this step, the investor has no security selection or asset allocation constraints. Here, we assume the risky asset the investor could invest is the most efficient market portfolio. This portfolio is approximated by the annualized return and standard deviation of the average S&P 500 index fund during 1997/1 through 2010/7, which yields an average return of 6.34 per cent and standard deviation of 16.55 per cent.

That is, S&P 500 average return and volatility are the inputs for risky asset return moments in equation (5). The glide path is also optimized in each period. The resulting equivalent consumption calculated in this step,  $\bar{C}_i^1$ , represents the hypothetical highest average welfare an investor  $i$  could realize.

*Step 2 – Risky portfolio constraint:* In this step, the investor is exposed to a risky portfolio (security selection) constraint. The risky asset he could invest is the actual offerings of the TDFs rather than the efficient market portfolio. Hence, we now solve the dynamic optimization problem described in equations (1)–(7) for each TDF series, with risky premium ( $\mu$ ) and standard deviation ( $\sigma_\eta$ ) of the risky asset replaced by those actually offered in the TDF series. In other words, Step 2 differs from Step 1 by using the actual TDF risky portfolios' return and risk data instead of the most efficient market portfolio. Appendix B discusses the process used to estimate the TDF risky portfolio return moments based on historical returns of individual risky assets under TDF. The annualized returns are after-expense returns. The consumption and asset allocation strategies in each time period are still optimally chosen. In this step, we derive the equivalent consumption  $\bar{C}_{i,j}^2$  for each investor  $i$  ( $i = 1 \dots 9$ ) using TDF series  $j$  ( $j = 1 \dots 36$ ) in our sample, and  $\bar{C}_i^1 - \bar{C}_{i,j}^2$  indicates the investor  $i$ 's welfare loss because of suboptimal risky portfolio in the TDF series  $j$ .

*Step 3 – Risky portfolio and glide path constraints:* Now investors in the market face both risky portfolio (security selection) and glide path (asset allocation) constraints; both their risky portfolio and glide path are dictated by the chosen TDF series. Specifically, we solve the dynamic optimization problem for each TDF series by using risky return and risk data of that particular TDF series as in Step 2. In addition, now we use the actual glide path of each TDF series (constructed as discussed in the section 'Data') instead of optimizing asset allocation in each period. In other words, Step 3 differs from Step 2 by using the actual

**Table 2:** Minimum welfare loss in whole sample and individual investor profiles (%)

	(1) Welfare loss from suboptimal risky portfolio	(2) Welfare loss from inappropriate glide path	(3) Total welfare loss
<i>Panel (A) Whole sample</i>			
	0.00	0.08	0.26
<i>Panel (B) Individual investor profiles</i>			
$\gamma = 8$	No high school	0.23	2.47
	High school	0.22	1.91
	College	0.12	0.52
$\gamma = 5$	No high school	0.19	0.45
	High school	0.15	0.24
	College	0.09	0.08
$\gamma = 2$	No high school	0.00	0.32
	High school	0.00	0.23
	College	0.00	0.18

Notes: This table shows the minimum welfare loss because of suboptimal risky portfolio in Column (1), welfare loss because of inappropriate glide path in Column (2) and total welfare loss in Column (3). Panel (A) shows the summary statistics in the whole sample including all nine investor profiles. Panel (B) summarizes the minimum statistics for each of the nine investor profiles.

$\alpha$  in each TDF series instead of optimizing it. The derived equivalent consumption in Step 3 is  $\bar{C}_{i,j}^3$ . Hence,  $\bar{C}_i^1 - \bar{C}_{i,j}^3$  captures an investor  $i$ 's total welfare loss by using TDF series  $j$ . Moreover,  $\bar{C}_{i,j}^2 - \bar{C}_{i,j}^3$  shows the additional welfare loss because of inappropriate glide path in the TDF series.

## RESULTS

### Welfare loss

For each investor  $i$  ( $i = 1 \dots 9$ ) choosing each of TDF series  $j$  ( $j = 1 \dots 36$ ), we numerically solve the optimization problem described in Step 1 through 3. Each of the nine investor profiles represents a combination of risk preference ( $\gamma = 2, 5$  and  $8$ ) and earning path for investors with different education background (no-high school, high school and college). In addition, the model described in the section 'Methodology' considers uncertainty in future labor income and risky asset return. Therefore, we conduct simulations for 10 000 investors to derive the equivalent consumptions  $\bar{C}_i^1, \bar{C}_{i,j}^2$  and  $\bar{C}_{i,j}^3$ . That is, we generate 10 000 simulation samples for each of the 657 profiles (nine investor profiles for Step 1 plus 36 TDF series

multiplied by nine investor profiles for Steps 2 and 3). Each simulation represents a different combination of labor income path and realized risky asset return. The average of these 10 000 possible outcomes represents the expected welfare loss of an average investor facing uncertainty. Loss can be divided into suboptimal risky portfolio ( $\bar{C}_i^1 - \bar{C}_{i,j}^2$ ) and inappropriate glide path ( $\bar{C}_{i,j}^2 - \bar{C}_{i,j}^3$ ). In the following, we present these welfare losses as percentages of equivalent consumption under the optimal portfolio in Step 1.

Welfare loss from suboptimal risky portfolio:

$$L_{i,j}^{12} = \frac{\bar{C}_i^1 - \bar{C}_{i,j}^2}{\bar{C}_i^1} \quad (9)$$

Welfare loss from inappropriate glide path:

$$L_{i,j}^{23} = \frac{\bar{C}_{i,j}^2 - \bar{C}_{i,j}^3}{\bar{C}_i^1} \quad (10)$$

Table 2 summarizes the minimum welfare loss an investor would take in the 36 TDFs under our analysis. Essentially these results represent the most optimistic scenario where each investor who is fully aware of his profile, characterized by income path and risk



preference, is free to choose any of the 36 TDFs available in the market, and the investor is capable of selecting the most appropriate TDF that fits his profile. Thus, Table 2 shows the welfare losses solely driven by the inefficiency in TDF design; we will further investigate welfare loss caused by mismatch between investors' profile and TDFs design in the sections 'Welfare loss – Failing to select the most appropriate TDF', 'Heterogeneity in TDF performance' and 'Risk-based selection strategy'.

Panel (A) in Table 2 reports the minimum welfare loss for all of the nine investor profiles. It shows that while an investor may completely avoid inefficiency in risky portfolio management, he always suffers from TDFs' inefficient glide path. As shown in Column (1), the best fund offering costs investors 0 per cent in suboptimal risky portfolio choice. That is, if the investor chooses the appropriate TDF that matches his characteristics, he does not suffer any welfare loss from inefficient management from the risky portfolio. However, the minimum glide path inefficiency caused 0.08 per cent of loss on annual consumption as shown in Column (2). Column (3) shows the minimum total welfare loss, the sum of losses from suboptimal risky portfolio and glide path inefficiency, costs an investor 0.26 per cent of annual consumption assuming the investor chooses the best offering among 36 TDFs.

In addition, minimum welfare loss changes across investor profiles. Panel (B) in Table 2 shows the welfare loss under each of the nine investor profiles, each representing a combination of risk preference ( $\gamma$ ) and education level. We find that welfare loss is generally less severe for risk-tolerant investors (the only exception being welfare loss from inappropriate glide path for investors with college education). For example, for high school graduates, a risk-tolerant investor ( $\gamma = 2$ ) incurs a minimum total welfare loss of 0.32 per cent of annual consumption compared with 2.64 per cent by a risk-averse

investor ( $\gamma = 8$ ). The finding agrees with Bodie and Treussard (2007). They employed a hypothetical glide path and ignored investors' periodical consumption choices. We complement their work with actual allocation strategies and consider investors' periodic consumption decisions. Our empirical examination concurs with their conclusion that TDFs generate more inefficiency for risk-averse investors because the market offerings are too aggressive. This aggressiveness perhaps is driven by the use of return-seeking strategies by TDF providers.

Table 2 also categorizes welfare loss by investors earning path proxied by education level: no-high school, high school and college. We find that having a higher education level helps alleviate welfare loss; investors with the lowest education level suffer the most from TDF inefficiency. For instance, at  $\gamma = 8$ , investors without a high school degree lose 3.21 per cent of annual consumption in total welfare, while investors with a college degree lose only 1.22 per cent with best TDF offering. Given that under-educated people are more likely to possess low incomes and low levels of financial knowledge, our finding implies that those with the least knowledge or inclination to understand TDFs are most likely to have substantial losses from TDF investment. Furthermore, Agnew *et al* (2011) found that low-income participants are more likely to use TDFs as their only investment in 401(k) plans. This further emphasizes the need of careful selection on TDFs for under-educated investors.

### **Welfare loss – Failing to select the most appropriate TDF**

The previous section quantifies TDF inefficiency by assuming that each investor is capable of selecting the most appropriate TDF that matches his profile from market offerings. In real life, investors may suffer from a second source of inefficiency: mismatch between investor's profile and TDF characteristics.

**Table 3:** Mean and maximum welfare loss in whole sample and individual investor profiles (%)

		(1). Welfare loss from suboptimal risky portfolio		(2). Welfare loss from inappropriate glide path		(3). Total welfare loss		(4). Welfare loss from inappropriate glide path/total welfare loss	
		Mean	Maximum	Mean	Maximum	Mean	Maximum	Mean	Maximum
<i>Panel (A) Whole sample</i>									
		0.59	2.32	1.73	17.12	2.33	17.97	67.54	100
<i>Panel (B) Individual scenarios</i>									
$\gamma = 8$	No high school	0.93	2.27	5.13	17.12	6.05	17.97	84.43	95.28
	High school	0.91	2.32	3.97	7.37	4.88	9.66	81.79	94.43
	College	0.48	1.21	2.84	6.42	3.32	7.38	84.01	95.43
$\gamma = 5$	No high school	0.86	2.15	0.89	1.91	1.75	3.88	54.15	81.03
	High school	0.74	1.86	0.71	1.83	1.44	3.43	51.47	82.84
	College	0.41	1.02	0.34	1.06	0.75	1.87	47.77	79.35
$\gamma = 2$	No high school	0.44	1.46	0.72	1.54	1.16	2.13	66.45	100.00
	High school	0.34	1.13	0.58	1.24	0.91	1.68	67.55	100.00
	College	0.22	0.74	0.44	0.91	0.66	1.20	70.21	100.00

*Notes:* This table shows the mean and maximum welfare loss because of suboptimal risky portfolio in Column (1), welfare loss because of inappropriate glide path in Column (2), total welfare loss in Column (3) and the ratio of total welfare loss explained by welfare loss from inappropriate glide path in Column (4). Panel (A) shows the summary statistics in the whole sample including all nine investor profiles. Panel (B) summarizes the mean and maximum statistics for each of the nine investor profiles.

That is, an investor may not be able to choose the most appropriate TDF to match his profile. For example, in DC plans, employees are not allowed to freely choose TDFs as only funds from one or two providers are offered. The low level of financial literacy among average American investors may hinder optimal investment decision even given full access to TDFs in the market.

To measure the actual welfare loss that could be taken by average investors, we first calculate the average and maximum welfare loss among various investor profiles given the 36 TDFs in the market. That is, instead of showing what an investor can achieve in the best case (minimum welfare loss shown in the section ‘Welfare loss’), we now calculate the average welfare loss assuming an investor is equally likely to invest in each of the 36 TDFs, and the maximum welfare loss assuming the investor unfortunately chooses the least appropriate fund.

Welfare loss reported in Table 3 has largely increased compared with the minimum welfare loss in Table 2. Welfare loss is modest if investors select the optimal TDF among current market offerings; however, investors may lose much more in real life when they fail

to take the appropriate TDF that matches their characteristics. Panel (A) in Table 3 summarizes the mean and maximum welfare loss over all of the nine investor profiles. As shown in Column (1), risky portfolio inefficiency on average causes 0.59 per cent of loss on annual consumption. This is a relatively modest loss compared with glide path inefficiency, which causes 1.73 per cent of loss on annual consumption as Column (2) shows. The welfare loss because of inappropriate glide path can be as high as 17.12 per cent of annual consumption in contrast with a maximum of 2.32 per cent because of suboptimal risky portfolio. The total welfare loss, the sum of losses from risky portfolio and glide path inefficiency, costs an average investor 2.33 per cent of annual consumption as shown in Column (3). More importantly, Column (4) indicates that 67.54 per cent of total welfare loss is attributed to inappropriate glide path.

This result bears an important implication: much of the practical attention is misallocated to improving risky portfolio performance, which in fact only accounts for less than a third of inefficiency. Inappropriate glide paths, on the other hand, hold a lion’s share of

inefficiency. Thus, investors' welfare would have more pronounced improvement from better glide path design.

Panel (B) in Table 3 shows the mean and maximum welfare loss under each of the nine investor profiles. It is found that current TDFs are more in favor to risk-tolerant investors and investors with the highest education level, which is consistent with findings in the section 'Welfare loss'. For certain investor profile, welfare loss from TDF investment can be substantial. For example, risk-averse investors ( $\gamma = 8$ ) with no high school education could lose up to 6.05 per cent of their annual consumption on average, and 17.97 per cent with the least appropriate TDF selected. In all 84.43 per cent of their total welfare loss is because of inappropriate glide path.

### Heterogeneity in TDF performance

In this section, we investigate how an employee's loss would vary with the TEF he chooses. We quantify this heterogeneity in performance in two ways: the difference between maximum and minimum losses (*Max-Min*) and the standard deviation (*Stdev*) of losses. We derive *Max-Min* and *Stdev* of the 36 TDF series for each of the nine investor profiles. For example, for an investor with high school education and  $\gamma = 5$ , we calculate the difference between the highest and lowest welfare losses and the standard deviation of welfares losses among 36 TDF series under analysis. For each welfare loss category (risky portfolio inefficiency, glide path inefficiency and total welfare loss), Figure 2 Panel (A) summarizes the average values of *Max-Min* and *Stdev* over the nine investor profiles.

We observe significant heterogeneity in TDF performance in Figure 2. For instance, Panel (A) shows that an average investor can reduce his loss in annual consumption by as much as 4.39 per cent (compared with an average total welfare loss of 2.33 per cent as in Table 3) when an appropriate TDF is selected. We find a more staggering result as we narrow the focus to risk-averse investors

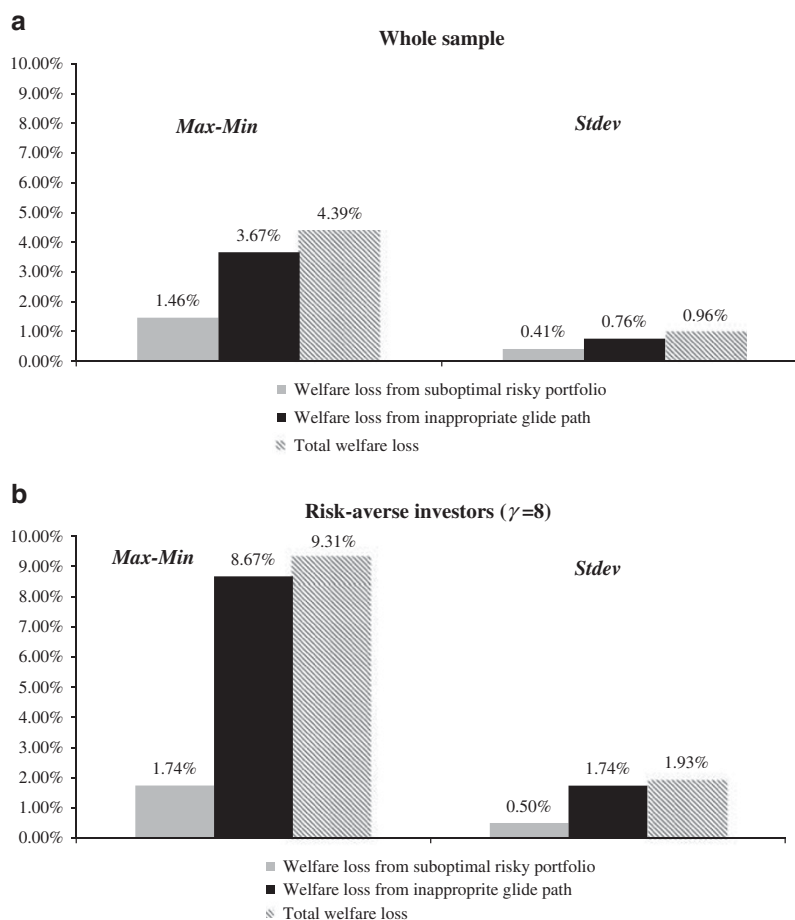
( $\gamma = 8$ ) in Panel (B). In this Panel, the average loss difference between the most and the least appropriate TDF soars up to 9.31 per cent.

We attribute TDFs' performance heterogeneity to variation in glide paths. This is evident from both *Max-Min* and *Stdev*. For example, as shown in Panel (A) in Figure 2, risky portfolio performance alone only generates 1.46 per cent of average *Max-Min* loss, while inefficiency in glide path pushes the average *Max-Min* loss to 3.67 per cent of annual consumption, more than two times higher. Similarly, glide path represents a much bigger variation measured by *Stdev*. The impact of glide path is even more pronounced among risk-averse investors ( $\gamma = 8$ ). The average *Max-Min* increases from 1.74 per cent for loss from suboptimal risky portfolio to 8.67 per cent with the contribution of inappropriate glide path.

Our numerical results quantify the heterogeneity in TDF performance. Evaluating and selecting a TDF based on its appropriateness is crucial to an investor's welfare. In the context of DC plans, it is common that employees are offered funds from a single TDF provider. If the fund happens to fit the employee's profile, he experiences relatively little loss in welfare. Otherwise, the investor experiences much higher loss. These are high stakes. Therefore it is crucial that plan fiduciaries understand the risk profile of participants in order to select appropriate TDFs. An immediate issue is to find a practically feasible strategy to achieve this goal, which will be explored in the next section.

### Risk-based selection strategy

In the previous section, we demonstrated the heterogeneity in TDF performance and emphasized the importance of selecting an appropriate TDF. Now we examine ways to rectify TDF inefficiency. Customized investment option for each investor seems to be an immediate remedy. However, a fully customized fund requires much time and cost, and hence is not likely to be feasible. Alternatively, Bodie and Treussard (2007)



**Figure 2:** Heterogeneity in TDF performance. (a) Whole sample; (b) Risk-averse investors ( $\gamma = 8$ ).

suggested offering a riskless investment together with a TDF. This strategy narrows the gap between risk exposure desired by an investor and the risk level a TDF provides. Nevertheless, this solution hinges on accurate understanding of TDFs' risk level, which is not generally an available information. Furthermore, the need to assess the gap between each investor's desired risk exposure and the risk level of TDF adds another level of difficulty.

In light of these challenges, we favor the *risk-based selection strategy* advocated by Viceira (2008) and Bruder *et al* (2012) as a better balance between theoretical ideal and practical barriers. This approach offers TDFs with three different risk levels: 'aggressive', 'moderate' and 'conservative', instead of

offering one life-cycle fund per target date. The simplicity in risk structure makes the match between TDFs' risk level and an investor's risk preference easy. Ease of implementation is always welcome, but how does the performance of this strategy compare with other strategies? In the following, we benchmark the performance of the *risk-based selection strategy* against two popular TDF selection strategies.

In practice, it is not unusual that a plan sponsor is short of resource to appraise or monitor TDFs. Instead, as industry experts pointed out during an interview with the US Government Accountability Office, plan sponsors, especially small ones, may arbitrarily choose a TDF in the marketplace. Most sponsors interviewed could not even

document that they had evaluated a range of investment managers in their TDF selection process. We refer to this as a *random selection strategy*. Even when plan sponsors attempt to select an appropriate TDF, they may find too little information to evaluate the appropriateness of the fund. Consequently, they may rely heavily on return-risk metrics, which is the predominant information industry reports provide for evaluating TDF performance (U.S. Government Accountability Office, 2011). We categorize this selection strategy – through which sponsors choose the TDF with the highest return – as a *return-based selection strategy*. For average individual investors, they are more prone to a *random* or *return-based selection strategy* because of fewer resources they have access to.

We measure the total welfare losses of the *random* and the *return-based selection strategies* and compare them with the loss of the *risk-based selection strategy*. For the *random strategy*, we randomly assign one of the 36 TDF series to an investor, and the same procedure is carried for each of the nine investor profiles. Then we derive the average outcome by averaging the total welfare losses over the nine investor profiles. For the *return-based strategy*, we assign the TDF series with the highest 2010 total return to each of the nine investor profile and calculate the average welfare loss. Last, we calculate the welfare loss under the *risk-based selection strategy*. Currently TDF providers do not disclose information on the target risk levels of their products. We construct the hypothetical ‘aggressive’ funds by selecting three TDFs with the lowest percentile of total welfare loss when  $\gamma$  equals 2. That is, we consider the top three TDFs for risk-averse investors ( $\gamma = 2$ ) as ‘aggressive’ funds. We also construct the hypothetical ‘moderate’ ( $\gamma = 5$ ) and ‘conservative’ ( $\gamma = 8$ ) funds in the same way. It is worth noting that the top performing funds under each risk category do not overlap, and therefore indicating that current market offerings do have various target risk groups.

Finally, we assign funds in each risk category to its target investors (‘aggressive’ funds to investors with  $\gamma = 2$  and so on) and calculate the average total welfare loss over the nine investor profiles.

Table 4 compares the average total welfare losses under the *random*, *return-based* and *risk-based selection strategies*. It shows that using a *random* or *return-based selection strategy* can result in substantial welfare loss, especially for risk-averse investors with low education level. For instance, the *return-based selection strategy* causes risk-averse investors ( $\gamma = 8$ ) without a high school degree 7.75 per cent loss in annual consumption on average. Surprisingly, the *return-based selection strategy* performs even worse than the *random selection strategy* under almost all of the nine investor profiles. We attribute this staggering loss to the mismatch between risk profiles of TDFs and individual investors. High returns are a consequence of high-risk exposure, which misaligns with the risk preference of investors.

Instead, an average investor choosing the *risk-based selection strategy* eliminates almost half of the losses that would otherwise be inflicted by a *random* or *return-based selection strategy*. The improvement is particularly substantial for risk-averse investors. For example, the average total welfare loss is as low as 1.63 per cent of annual consumption for investors with college degree and  $\gamma = 8$ . In contrast, the same investors’ losses from the *random* and *return-based selection strategies* are more than doubled at 3.32 and 3.41 per cent, respectively.

Therefore, the *risk-based selection strategy* offers a cost effective solution to TDF inefficiency. By assessing an individual investor’s risk preference level and matching him with an appropriate TDF, plan sponsors or investors themselves could significantly improve fund efficiency. For TDF providers, such offerings also expand their target consumer groups while causing less suffering from misuse of their products. In addition, our results make investors and plan sponsors, especially small ones, aware of the potential

**Table 4:** Total welfare loss from random, return-based and risk-based selection strategies (%)

	<i>No high school</i>	<i>High school</i>	<i>College</i>
<i>Panel (A) Random selection strategy</i>			
Mean total welfare loss	2.33		
$\gamma = 8$	6.05	4.88	3.32
$\gamma = 5$	1.75	1.44	0.75
$\gamma = 2$	1.16	0.91	0.66
<i>Panel (B) Return-based selection strategy</i>			
Mean total welfare loss	2.54		
$\gamma = 8$	7.75	4.79	3.41
$\gamma = 5$	1.81	1.52	0.79
$\gamma = 2$	1.18	0.92	0.66
<i>Panel (C) Risk-based selection strategy</i>			
Mean total welfare loss	1.22		
$\gamma = 8$	3.34	2.88	1.63
$\gamma = 5$	0.83	0.61	0.31
$\gamma = 2$	0.57	0.46	0.37

*Note:* This table shows the mean total welfare loss by following random selection strategy in Panel (A), return-based selection strategy in Panel (B) and risk-based selection strategy in Panel (C). In each Panel, the mean total welfare loss in the whole sample including all nine investor profiles is first provided. It is followed by the mean statistics for each of the nine investor profiles.

**Table 5:** Welfare loss using 1926–2010 data (%)

	<i>(1) Welfare from suboptimal risky portfolio</i>	<i>(2) Welfare loss from inappropriate glide path</i>	<i>(3) Total welfare loss</i>	<i>(4) Welfare loss from inappropriate glide path/total welfare loss</i>
Mean	0.62	1.35	1.96	67.60
<i>Max-Min</i>	2.22	3.17	3.41	
<i>Stdev</i>	0.53	0.64	0.79	
<i>Selection strategy</i>				
Random			1.96	
Return-based			1.99	
Risk-based			0.98	

*Note:* This table first shows the mean values of welfare loss because of suboptimal risky portfolio in Column (1), welfare loss because of inappropriate glide path in Column (2), total welfare loss in Column (3) and ratio of total welfare loss explained by welfare loss from inappropriate glide path is reported in Column (4). The table then summarizes the average values of *Max-Min* and *Stdev* over the nine investor profiles. Last, it shows the mean total welfare loss by following random selection strategy, return-based selection strategy and risk-based selection strategy.

danger from using a *random* or *return-based selection strategy*.

### Welfare loss based on 1926–2010 data

The analysis above is based on risky and riskless returns estimated during the period of 1997/1–2010/7. To exclude the possibility that our results are mainly driven by this specific time period, we run the robustness test using return estimates during the period

of 1926/7–2010/7. The annualized return and standard deviation of the average S&P 500 index fund during this longer period are 11.08 and 19.38 per cent, respectively. The average annual T-bill return is 3.58 per cent. We also re-estimate the TDF risky portfolio return moments based on 1926/7–2010/7 data.

The results based on 1926/7–2010/7 data, when compared with our original findings, do not reveal any substantial differences. For example, we first calculate the mean values of

welfare loss because of suboptimal risky portfolio, welfare loss because of inappropriate glide path, total welfare loss and ratio of total welfare loss explained by welfare loss from inappropriate glide path over the nine investor profiles. As shown in Table 5, inappropriate glide path constitutes the major source (67.60 per cent) of TDF performance inefficiency. This inefficiency could reduce an investor's annual consumption by 1.35 per cent on average.

We also calculate the average *Max-Min* and *Stdev* over the nine investor profiles as in the section 'Heterogeneity in TDF performance'. Heterogeneity in TDF performance is significant, with average difference between maximum and minimum total welfare losses being 3.41 per cent. Such heterogeneity is primarily caused by variation in glide paths. Last, we confirm that risk-based selection strategy could reduce approximately half of the welfare loss suffered from random or return-based strategies using 1926–2010 data.

## CONCLUSION

We use the actual return-risk metrics and glide paths to evaluate the efficiency of 36 TDF series available in the third quarter of 2010. Our assessment distinguishes between the effects of suboptimal risky portfolio and inappropriate glide path. We find that 67.54 per cent of the total welfare loss is attributed to inappropriate glide path. We estimate that inefficiency because of glide path can reduce consumption of an investor by as high as 17.12 per cent per year, contrasting a maximum of 2.32 per cent loss because of suboptimal risky portfolio. Moreover, we find substantial heterogeneity in TDF performance that is mainly caused by variation in glide paths. In other words, there is no single glide path that is the best for everyone.

For that reason, we advocate the *risk-based selection strategy* to alleviate TDFs' inefficiency. This strategy aligns the risk level offered by

funds with investors' risk preference. Under this strategy, TDF providers offer funds with various risk levels, such as 'aggressive', 'moderate' and 'conservative', which allow investors to select funds based on their risk preference. We estimate that a *risk-based selection strategy* can eliminate half of the welfare loss caused by other commonly used strategies.

The implementation of a *risk-based selection strategy*, however, requires disclosure of investment objective and philosophy from TDF providers. The joint public hearing by SEC and the Department of Labor in 2010 indicated the need of wider public understanding of TDFs, and hence stimulating improvement on TDF transparency. Yet, the resulting transparency centers around asset allocation strategies. Other essential elements to promote a *risk-based selection strategy*, such as funds' target risk level, remain unfortunately opaque (Sandhya, 2010; U.S. Government Accountability Office, 2011). Hence, another step of policy support for TDF transparency is required to implement a *risk-based selection strategy*.

In addition, our results demonstrate the need for better TDF assessment tools. We show that glide paths are dominant determinant of TDF efficiency. Thus, the appropriateness of glide paths warrants considerable attention in TDF evaluation. Yet, current TDF assessment still mainly relies on return-risk metrics, leaving appropriateness of glide paths ignored. This ignorance may be attributed to financial professionals' reluctance to adopt contemporary asset allocation models. In a comprehensive survey of private wealth managers, Schroder (2013) found that, while wealth advisors are aware of the limitations of traditional investment concepts, such as the static mean-variance analysis, they do not make extensive use of new dynamic asset allocation models; truly customized financial advice that incorporates the client's human capital, spending objectives and investment time horizon is offered only by a minority of

practitioners. Some of this reluctance could be because of the lack of practical models and tools that incorporate insights of rigorous economic theory. Although this study has initiated the evaluation method incorporating pioneering work on life-cycle optimization theory, more work must be done to develop more practical techniques and models for practitioners to use.

Last, there are other areas of further improvements. For example, Yoon (2010) introduced a new approach to define TDF glide path by explicitly incorporating the current term structure of risk. He also suggested a dynamic asset allocation strategy that considers the time-varying market risk. Further studies could broaden the scopes of asset returns in the analysis by incorporating time-varying returns and intertemporal hedging strategy in the model. In this article, we also assume that TDFs do not change their investment strategies through time when we derive the glide path of each TDF series. With more TDFs data, another productive avenue for future inquiry would be to explore TDFs' performance based on funds' actual glide path through time.

It is also important to highlight the limitation of this study. First, our evaluation results are based on Cocco *et al* (2005) model. While this model is widely used in the multi-period life-cycle optimization literature, our results may change if different models are adopted. For example, we do not consider labor supply flexibility and bequest motive in the model. While conjecture that including additional factors would not significantly change our conclusion regarding heterogeneity of funds performance, the absolute value of investors' welfare loss could be changed. In addition, the welfare loss reported in the article is based on the assumption that investors have all their financial assets invested in TDFs. It is possible that investors may have other investments outside TDFs. Therefore caution should be taken before any broad recommendations are made.

## NOTE

1. Out of 277 funds in our sample, we were only able to obtain return data on 239 funds.

## REFERENCES

- Agnew, J.R., Szykman, L.R., Utkus, S.P. and Young, J.A. (2011) What People Know about Target-Date Funds: Survey and Focus Group Evidence. Chestnut Hill, MA: Financial Security Project. FSP Working Paper no. 2011-2.
- Balduzzi, P. and Reuter, J. (2012) Heterogeneity in Target-Date Funds and the Pension Protection Act of 2006. Cambridge, MA: National Bureau of Economic Research. NBER Working Paper no. 17886.
- Bodie, Z. (2003) Thoughts on the future: Life-cycle investing in theory and practice. *Financial Analysts Journal* 59(1): 24-29.
- Bodie, Z. and Crane, D.B. (1997) Personal investing: Advice, theory, and evidence. *Financial Analysts Journal* 53(6): 13-23.
- Bodie, Z., Merton, R.C. and Samuelson, W.F. (1992) Labor supply flexibility and portfolio choice in a life cycle model. *Journal of Economic Dynamics and Control* 16(3-4): 427-449.
- Bodie, Z. and Treussard, J. (2007) Making investment choices as simple as possible, but not simpler. *Financial Analysts Journal* 63(3): 42-47.
- Bridges, B., Gesumaria, R. and Leonesio, M.V. (2010) Assessing the performance of life-cycle portfolio allocation strategies for retirement saving: A simulation study. *Social Security Bulletin* 70(1): 23-43.
- Bruder, B., Culerier, L. and Roncalli, T. (2012) How to Design Target-Date Funds? Paris, France: Lyxor Asset Management. The Lyxor White Paper no. 9.
- Campbell, J.Y., Cocco, J.F., Gomes, F.J. and Maenhout, P.J. (2001) Investing retirement wealth. In: J.Y. Campbell and M. Feldstein (eds.) *Risk Aspects of Investment-Based Social Security Reform*, Chicago: University of Chicago Press.
- Cardak, B.A. and Wilkins, R. (2009) The determinants of household risky asset holdings: Australian evidence on background risk and other factors. *Journal of Banking & Finance* 33(5): 850-860.
- Cocco, J.F., Gomes, F.J. and Maenhout, P.J. (2005) Consumption and portfolio choice over the life cycle. *The Review of Financial Studies* 18(2): 491-533.
- Gomes, F.J., Kotlikoff, L.J. and Viceira, L.M. (2008) Optimal life-cycle investing with flexible labor supply: A welfare analysis of life-cycle funds. *American Economic Review: Papers & Proceedings* 98(2): 297-303.
- Horneff, W., Maurer, R.H. and Rogalla, R. (2010) Dynamic portfolio choice with deferred annuities. *Journal of Banking & Finance* 34(11): 2652-2664.
- Investment Company Institute (2011) 2011 investment company fact book, [http://www.ici.org/pdf/2011\\_factbook.pdf](http://www.ici.org/pdf/2011_factbook.pdf), accessed 1 April 2015.
- Israelsen, C.L. and Nagengast, J.C. (2012) Popping the hood V, 2012. An analysis of target date fund families, [https://www.americancentury.com/pdf/Popping\\_the\\_Hood\\_Study\\_2012.pdf](https://www.americancentury.com/pdf/Popping_the_Hood_Study_2012.pdf), accessed 21 April 2014.
- Jagannathan, R. and Kocherlakota, N.R. (1996) Why should older people invest less in stocks than younger people? *Federal Reserve Bank of Minneapolis Quarterly Review* 20(3): 11-23.



- Mitchell, O.S. and Utkus, S.P. (2012) Target-Date Funds in 401(k) Retirement Plans. Philadelphia, PA: Pension Research Council. Pension Research Council Working Paper no. 2012-02.
- Morningstar (2011) Target-date series research paper: 2011 industry survey, [http://corporate.morningstar.com/us/documents/MethodologyDocuments/MethodologyPapers/Target\\_Date\\_Industry\\_Survey\\_2011.pdf](http://corporate.morningstar.com/us/documents/MethodologyDocuments/MethodologyPapers/Target_Date_Industry_Survey_2011.pdf), accessed 5 March 2014.
- Morningstar (2013) Target-date series research paper 2013 survey, <http://corporate.morningstar.com/us/documents/ResearchPapers/2013TargetDate.pdf>, accessed 5 March 2014.
- Pang, G. and Warshawsky, M. (2011) Target-date and balanced funds: Latest market offerings and risk-return analysis. *Financial Services Review* 20(1): 21–34.
- Poterba, J., Rauh, J., Venti, S. and Wise, D. (2009a) Lifecycle asset allocation strategies and the distribution of 401(k) retirement wealth. In: D. Wise (ed.) *Developments in the Economics of Aging*, Chicago: University of Chicago Press.
- Poterba, J., Rauh, J., Venti, S. and Wise, D. (2009b) Reducing social security PRA risk at the individual level-lifecycle funds and no-loss strategies. In: J. Brown, J. Liebman and D.A. Wise (eds.) *Social Security Policy in a Changing Environment*, Chicago: University of Chicago Press.
- Sandhya, V.V. (2010) Agency problems in target-date funds, <http://ssrn.com/abstract=1570578>, accessed 21 April 2014.
- Schroder, D. (2013) Asset allocation in private wealth management: Theory versus practice. *Journal of Asset Management* 14(3): 162–181.
- U.S. Government Accountability Office (2011) Defined Contribution Plans—Key Information on Target Date Funds as Default Investments Should be Provided to Plan Sponsors and Participants. Washington, DC: GAO Report to Congressional Requesters GAO-11-118.
- U.S. Dept. of Labor (2012) Private Pension Plan Bulletin: Abstract of 2010 Form 5500 Annual Reports. U.S. Department of Labor Employee Benefits Security Administration, Washington DC.
- VanDerhei, J., Holden, S., Alonso, L. and Bass, S. (2012) 401(k) Plan Asset Allocation, Account Balances, and Loan Activity in 2011. Washington, DC: Employee Benefit Research Institute Brief Issue no. 380.
- Viceira, L.M. (2008) Life-cycle funds. In: A. Lusardi (ed.) *Overcoming the Saving Slump: How to Increase the Effectiveness of Financial Education and Saving Programs*, Chicago: University of Chicago Press.
- Yoon, Y. (2010) Glide path and dynamic asset allocation of target date funds. *Journal of Asset Management* 11(5): 346–360.

## APPENDIX A

### Appendix A Numerical solution method

Our dynamic programming model was solved using backward induction. The state variables in each period (age) include the cash-on-hand

at the beginning of each period and the transitory shock. In the last period, the agent simply consumes all cash-on-hand and generates the value function from that consumption. This value function is then used to compute the policy rules, and the corresponding value function, for the previous period. This process is carried out from the last period to the first period.

We obtained the optimal decision variables (consumption and portfolio allocation) in an unconstrained problem using Nelder–Mead method. When the unconstrained solution generated by Nelder–Mead method is infeasible, we applied a standard grid search to the constrained problem. We also applied standard grid search in several fund family and confirmed that Nelder–Mead method generates global optimal. Then Nelder–Mead is used throughout all of the remaining fund families for computational efficiency. The state-space was discretized using power grid in which the ratio of two adjacent state variables equals to a chosen power parameter. The upper and lower bounds for state-space were chosen to be non-binding in all periods. Gauss–Hermite quadrature method is used to approximate the density functions for innovation to excess stock returns, labor income shock and transitory shocks to perform numerical integrations. In evaluating the value function that corresponds to state variables that do not lie in the chosen grid points, we used a cubic spline interpolation in the log of the state variables.

## APPENDIX B

### Estimating TDF risky portfolio return moments

To compute return moments of risky portfolios under each TDF, we adopt the CAPM asset pricing model and regress the excess return of each equity asset under the TDFs on market portfolio – S&P 500

index:

$$R_{i,t} = \beta_i MKT_t + \varepsilon_{i,t}, \quad (B.1)$$

where  $R_{i,t}$  is the excess return for equity asset  $i$  at time  $t$ ;  $MKT$  is the excess return for S&P 500. The time period for regression is 1997/1–2010/7 (or less if not available for some equities). Using the estimated risk loading  $\hat{\beta}$  from the regression above, we can estimate moments for each equity asset as:  $\hat{\mu}_f = \hat{\beta}'\hat{\mu}$ ,  $\hat{\Sigma}_f = \hat{\beta}'\hat{\Sigma}\hat{\beta} + \hat{\Sigma}_{idio}$ , where  $\hat{\mu}_f$  is the vector of estimated mean excess return over all equity assets;  $\hat{\Sigma}_f$  is the estimated variance-covariance matrix of excess returns over all equity assets;  $\hat{\mu}$  and  $\hat{\Sigma}$  are the mean excess return and variance of market portfolio (S&P 500); and  $\hat{\Sigma}_{idio}$  is the idiosyncratic risk

estimated from the variance-covariance matrix of regression residuals  $\varepsilon_{i,t}$ .

Now, based on the estimated mean and variance of returns over all equity assets, we estimate moments of risky portfolio in each TDF:

$$\hat{\mu}_p = \omega' \hat{\mu}_f - e_p \quad (B.2)$$

$$\hat{\Sigma}_p = \omega' \hat{\Sigma}_f \omega \quad (B.3)$$

where  $\omega$  is the weight vector over individual equity assets in the risky portfolio of a particular TDF fund. The risky portfolio return is adjusted for TDF expense  $e_p$ . Last, the average risky portfolio returns and standard deviations across all TDFs in one series is used as the return-risk measures for risky portfolio in that TDF series.