Target Date Funds and Retirement Savings

March 2010

A study by Deloitte Financial Advisory Services LLP in conjunction with Advanced Analytical Consulting Group Inc. for the U.S. Department of Labor, Employee Benefits Security Administration.

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Introduction

Target Date Funds ("TDFs", also known as life cycle funds) have become an important component of individual retirement decisions. TDFs are investment vehicles that invest their assets into other mutual funds. A key aspect of TDFs is that the asset allocation changes over time such that the investment risks diminish as the fund's target date approaches. For example, a lifecycle fund with a 2030 target year is generally marketed to Defined Contribution ("DC") plan participants who aim to retire around 2030. Its investment strategy would become more conservative as the target date approaches. The underlying idea is that the risk workers should take on should diminish as their investment horizon shortens.[1] Some of the earliest TDFs were developed in the mid-1990s and many fund managers now offer a series of lifecycle funds. Evidence suggests that 70 percent of U.S. employers now use target-date funds as their default investment (Collins, 2009). The Thrift Savings Plan, a DC plan for federal employees, added life cycle funds to its investment options in 2005.

Typically, DC plan participants have choices over how to invest their retirement assets, in stocks, bonds, money market funds and mutual funds. The purpose of the work described in this report is to gain a better understanding of how TDFs can affect the accumulation of retirement wealth compared to other asset holdings. To that end, the U.S. Department of Labor ("DOL") requested that we use the micro-simulation model PENSIM to examine the distribution of DC benefits accumulated by investors under various asset allocation strategies.

1. Background

As noted above, TDFs were first offered in the 1990s and have grown steadily in popularity. Recent estimates suggest that over $227 billion dollars are invested in these types of funds (Donahue 2009). The Pension Protection Act of 2006 (PPA) designated target-date funds as one of the qualified default investment alternatives (QDIAs). In December 2008, 31 percent of 401(k) participants held TDFs (VanDerhei, et al. 2009).

TDFs have a common feature of a predetermined declining equity exposure as the participant approaches the target retirement date. In practice, there are significant differences in the equity glide paths chosen by different fund families and offered by different plans. Our earlier research for EBSA on actual funds suggested that TDFs generally have over 90 percent equity exposure several decades before the target date, declining to 20 to 60 percent at the target dates.

Several papers have used stochastic simulation models to examine, among other things, the role of TDFs in the accumulation of retirement wealth. One of the key papers on this topic is Holmer (2009a). This paper utilizes the PENSIM software to conduct the analysis. Under different assumptions of assumed risk aversion and different TDF asset

[1] See Viceira (2009) and Kintzel (2007) for a general description of the underlying characteristics of TDFs.

allocation assumptions, Holmer simulates risk-adjusted retirement (OASDI, DB and DC) and pension (DB and DC) benefits at age 70 for a U.S. cohort born in 1990. It is important to note that our work utilizes many of the same methodological, individual and macroeconomic assumptions as presented in this paper. There are a number of important findings in this paper. Holmer finds, for example, that the highest risk-adjusted pension benefit is obtained when following a rule that mimics actual TDFs—equity investment shares of 75 to 80 percent at age twenty declining to 30 to 35 percent at age 65. He also finds that at lower levels of risk aversion, risk-adjusted pension benefits are greater when there is a greater share of equities available in the life cycle fund. Expanding the analysis to include OASDI, he finds that the low risk associated with these benefits suggests that higher overall risk-adjusted benefits can be found by taking on more risk in the other investment components (i.e., a higher equity percentage in the life cycle fund).

Another paper that is similar to our work is Poterba et al. (2005). In this paper the authors consider how different asset allocation strategies impact the retirement wealth and expected utility of wealth for a cohort of individuals in the Health and Retirement Study. Like the analysis we present below, the authors consider a variety of possible asset allocation rules including ones that include only one asset (100 percent inflation-indexed bonds, long-term government bonds, or corporate stock), ones that include a mixture of two assets using a simple allocation rule (i.e., equity percent equals 110 minus age of household head), and ones based on actual TDFs available in the market. Interestingly, their simulated wealth measures suggest that allocating 100 percent in equities leads to the greatest wealth at retirement. They also suggest, however, that their results are sensitive a number of the parameters including the assumed return on equities. TDFs, on the other hand, appear to perform about as well as simpler asset allocations in which the equity exposure over time is equal to the average of that found in a market TDF.

Finally, Pang and Warshawsky (2009) use a stochastic simulation model to consider the risk and return tradeoffs of life cycle funds. An interesting feature of their paper is that they consider five different actual TDFs for analysis. They recognize that not all TDFs are the same even if they have the same target date. The funds are chosen for analysis by specific percentiles of equity share (95^{th}, 75^{th}, 50^{th}, 25^{th}, and 5^{th} percentiles) out of all funds available on a selected date. They focus on the wealth and level of risk at age 65 for individuals who invested in TDFs early in their careers, in the middle of their careers, and at retirement. One of their results suggests that TDFs are not without risk and there is variation in the risk levels across the various funds.

2. The PENSIM Software

Overview of the PENSIM software

As directed by DOL, this project uses the software developed by the Policy Simulation Group ("PSG") for producing estimates of individual benefits under the employer-sponsored pension system in the US.[2] Our analyses mainly use two of the PSG's three computer simulation models. SSASIM provides the "projections of key macrodemographic and macroeconomic assumptions, as in the 2009 OASDI Trustees Report." The second model, PENSIM, uses the SSASIM macro projections to microsimulate the accumulation patterns of a cohort of individuals covered by employer-sponsored pensions. The third model, GEMINI, was used in the simulations only to obtain certain pension related outputs.

The models consist of numerous equations that predict marriage, employment, job changes, pension plan availability, death and other outcomes for each individual. Additionally, the models project annual rates of return on assets chosen by the individual as well as contributions and withdrawals. In its simplest form, each run of the PENSIM model, with macro conditions projected from SSASIM for each year of the simulation, produces paths of employment income, pension wealth from various sources and other financial measures over time for each individual. Many of these quantities can be accessed from the various output tables.

We use the functionality of the PSG models that allows multiple-scenario runs that simulate the outcomes for each individual under "stochastic pension environments." The values of the macrodemographic and macroeconomic variable change across the various scenarios, which may be interpreted as future states of the world. This generates a number of possible paths for each individual. Specifically, fifteen major variables are assumed to be stochastic: total fertility rate, net immigration flow, mortality decline rate, female and male labor force participation rates, unemployment rate, inflation rate, productivity growth rate, wage share growth rate, hours worked growth rate, nominal interest rate on Treasury bonds, disability incidence rate, disability recovery rate, equity return, and the rate spread between Treasury bills and Treasury bonds.[3] Macroeconomic scenarios result in different pension wealth accumulation outcomes because of variation in rates of return on equity and bonds, but also because different economic conditions affect wages and DC plan contributions. Much of our analysis studies the differences in the distributions of pension wealth accumulation across 500 scenarios with different macro conditions.[4]

Our analysis focuses on the effects of TDFs, as compared to other investments, on the accumulation of DC pension benefits. We ignore the wealth accumulated through the Social Security system and wealth from defined benefit ("DB") pension plans.[5] As a

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[2] Description of software is drawn from Holmer (2009b). In particular, we use the the standard version of December 18, 2009. Our use of the PSG models described herein was at the direction of DOL.
[3] See Holmer (2009d), page 11.
[4] These 500 scenarios represent a sample of potential states of the macro economy; they do not represent all potential states of the world. It is conceivable that under certain other scenarios, our findings might be different.
[5] In the PSG models, employers' offerings of DB and DC plans are exogenous to the individual (that is, workers do not sort into jobs that offer particular pension plans). Additionally, retirement decisions are assumed not to depend on accumulated retirement wealth. Under these conditions, we assume that DB and Social Security wealth are exogenous or held constant for the individual and we are comfortable focusing on differences in DC pension accumulations.

result, our analysis is not a complete accounting of the accumulated retirement wealth of individuals.

In general, we make very few changes to the parameter values in the baseline equations in the PSG models. We change the specifications of investor styles, described in detail below, but otherwise run the models with their default parameter values. A sensitivity analysis of the underlying models and verification of parameter choices is beyond the scope of this paper.

Investment options

PENSIM allows for a variety of equity and debt investment options. SSASIM uses historical data to estimate the parameters that determine the cyclical dynamics of four stochastic macroeconomic variables— the inflation rate, the nominal yield on Treasury bonds, the return on equities, and the yield spread between Treasury bills and Treasury bonds— that determine asset returns. Cyclical fluctuations in these four macroeconomic variables are generated using a vector-autoregressive model with a two-year lag structure, a VAR(2) model, the parameters of which are estimated with annual historical data.[6]

Table 1 below summarizes the characteristics of available investment options.

Table 1: Asset Characteristics

Asset Class	Base Return*	Asset Fee	Shock to Return Mean	Shock to Return Std Dev
Equity Index Fund (EIF)	S&P500	0.45%		
Diversified Equity Fund (DEF)	S&P500	1.00%	0	1%
Portfolio of stocks (Stocks)	S&P500	**	0	10%
Government Bond Fund (GBF)	T-Bonds	0.45%		
Money Market Fund (MMF)	T-Bills	0.45%		
Target Date Fund	Depends***	0.75%		

* SSASIM generates fixed-income base returns based on intermediate assumptions of the 2009 OASDI Trustees Report. Equity base returns are assumed to be 2.0 percent above T-Bonds returns, on average.
** The Stocks portfolio is used only as part of TDFs with a 0.75% asset fee.
*** TDF return depends on the age-specific mix of assets held in the fund.

Equities: The equity investments range from a portfolio of relatively few stocks, to a fund that is diversified but not as much as the Standard and Poor's 500 ("S&P500") index, to an equity index fund that mimics the S&P500. The S&P500 returns are generated as described above. The less diversified equity options have returns that are equal to the S&P500 return plus a shock (e) drawn from a distribution that can be specified by the user. Table 1 shows the default distributions used in PENSIM and suggests a wider variance for less diversified holdings.

[6] See Holmer (2009d), page 14. The PENSIM user may change these parameters.

Debt: US Treasury bills and bonds are available. The returns on T-Bonds are generated as described above; T-Bill returns are a fraction of T-Bond returns.

TDFs: TDFs are age-variant portfolios of equities and debt. TDFs can hold T-Bills, T-Bonds, Equity Index Fund, and a portfolio of stocks specific to the TDF, where the weights on each asset can change as the holder ages. The return on a TDF in any year depends on the specific mix of assets in the fund.

Each individual holding a particular asset realizes the same annual return on the asset. No asset beats the market (i.e., S&P500) consistently. In the stochastic runs, 500 macro scenarios are characterized by different values of asset rates of return, inflation and other variables drawn from distributions embedded in the SSASIM module. The macro draws affect the real returns on the asset holdings over the individual's lifetime and, therefore, her accumulated retirement wealth.

3. Descriptions of Scenarios and Investor Styles

<u>Specifications of Macro Scenarios and Investor Styles</u>

Each simulation selects a 0.5% sample of individuals from the 1995 birth cohort, or about 30,000 individuals whose lifecycle and employment outcomes and asset returns are generated by PENSIM. In the stochastic runs, individual outcomes are generated for 500 macro scenarios using a Run Specification File (.rsf) in the standard version of PENSIM.

We investigate the effects of various investment strategies by assigning individuals to investor Styles that we specify. PENSIM allows up to four Styles to be specified in each run and a probability of assignment to each Style.[7] Our strategy is to run different sets of macro scenarios with all individuals assigned to one Style and compare outcomes across runs. This has several advantages. First, we can specify more than four Styles. Second, it is not necessary to specify the fraction of individuals in each Style. Third, we observe the full sample of 30,000 individuals in each Style. One disadvantage of our approach is that we cannot easily combine our sets of investors to represent the population or mimic the aggregate asset allocations of DC plan investors in the US.

<u>Sources of Variation in Pension Outcomes</u>

Across 500 macro scenarios there are two principal types of variation in the individual's accumulation of DC benefits. First, there are different future states of the world (macro environments) as described earlier that affect rates of return. The SSASIM software generates different values for each macro variable for each scenario. Second, across macro scenarios, individuals realize different outcomes for education, income, death date

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[7] In the PENSIM module, the Style definitions are found in the *ACCTAA1, ACCTAA2, ACCTAA3,* and *ACCTAA4* tables, which allows the user to specify asset allocation weights at various ages; TDFs are specified in Assets *tdf_aa_id*. The probabilities for assignment into each Style are specified in *AA_PROB* table and can change over calendar years. The individual's Style is fixed over her lifetime, but the Style definition is very flexible and allows for a number of investment strategies to be modeled. PENSIM's baseline Style definitions and their probabilities produce aggregate asset allocations similar to that found in a very large sample of 401 plans (Holmer (2009c), page 226).

and other lifecycle and employment outcomes. This prevents a comparison of individual outcomes across macro scenarios, because important characteristics of the individuals vary across macro scenarios. In other words, each macro scenario in effect represents a different sample of individuals experiencing the specific macro conditions in that scenario. In particular, the plan contributions made by a specific individual differ across macro scenarios. In what follows we compare the outcomes for all samples of individuals across macro scenarios while only focusing on differences generated by the macro variables and ignoring other differences across individuals.[8]

When we change the investor style across runs, the individual's lifecycle and employment outcomes are fixed for each macro scenario. For example, in one comparison below, we assign all individuals to a fund filled only with T-Bonds and run 500 macro scenarios. In another run, we assign all individuals to an equity index fund and run the same 500 macro scenarios. Individual lifecycle and employment outcomes are the same, macro scenario by macro scenario, while the DC benefit accumulation changes according to the asset holdings and the macro influences on the returns for that asset. This allows comparisons at the individual level across the Style assignments in different runs, but as mentioned above not across macro scenarios within the same run.

Investor Styles

The table below defines our investor Styles, which are characterized by the fraction of the individual's DC pension wealth in each asset class at each age.[9]

Table 2: Asset Allocation by Investor Style

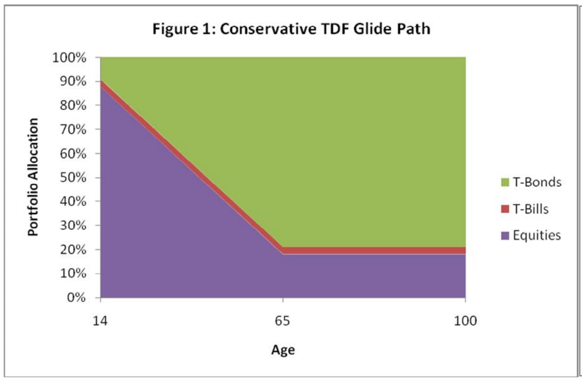
	1: DEF	2: GBF	3: EIF	4: DEF+ GBF	5: MMF +GBF	6: TDF Conservative		7: TDF Aggressive	
Age						14	65	14	65
Equity Index Fund (EIF)			100%						
Diverstified Equity Fund (DEF)	100%			50%					
Money Market Fund (MMF)					50%				
Government Bond Fund (GBF)		100%		50%	50%				
Target Date Fund						100%	100%	100%	100%
GBF						9%	79%	9%	39%
MMF						3%	3%	3%	3%
EIF						44%	9%	44%	29%
Stocks						44%	9%	44%	29%

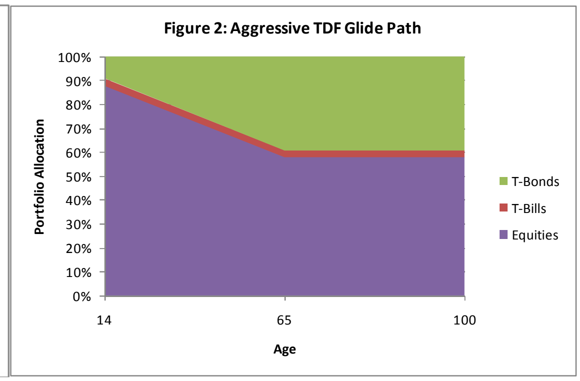
[8] In essence, this means that the sample of individuals changes across macro scenarios. This feature where individual lifecycle and employment outcomes change across macro scenarios may prevent some types of analyses of interest to some researchers.

[9] In PENSIM, the individual is assumed to rebalance her portfolio to achieve the defined mix at each age, rather than change the flow of contributions and withdrawals to achieve the defined mix over time.

Styles 1 through 3 represent single-asset investors who choose the same asset over their investing lifetimes. Styles 4 and 5 are investors who split their assets between a diversified equity fund and either money market funds or government bond funds, with the same weighting between the two assets over their investing lifetime.

We construct two TDF options. The conservative TDF (Style 6) starts out heavily invested in equities (44% in equity index fund and 44% in other stocks) and the equity fraction declines linearly over time until age 65 when the equity fraction is 18%. The aggressive fund (Style 7) starts out with the same allocation as the conservative TDF, but stays more heavily weighted in equities, achieving 58% in equities by age 65. The glide paths for each of the TDF options are shown in Figures 1 and 2.[10]





4. Results of Scenario Analyses

Metrics and Methods

The measure of pension wealth we use in our analysis is the present value at age 65 of DC pension benefits expressed in 2009 dollars; the cohort in our analysis, born in 1995 reaches age 65 in the year 2060. In the PSG models, this is variable *ipvpb* and it represents the present value of the individual's lifetime stream of DC pension benefits as of age 65 (plus her DB cash balance accumulations, which tend to be small and are inseparable from the DC benefits in the PSG models).

In each macro scenario and for each investor Style, some fraction of individuals accumulate no DC pension wealth because their employers do not offer such plans, or investors switch employers and cash out their rollover balance, or, in a very small number of cases, the investor's contributions are small and the returns are poor enough to zero out her balance by age 65. In what follows, we account only for workers with positive DC pension benefits.

Our primary interest is in DC pension benefit differences due to investor styles. We therefore suppress differences across individuals of a cohort by computing a summary statistic (mean, median, 10th percentile, 25th percentile) across individuals and comparing

[10] In PENSIM, investors are assumed to convert their accumulated DC pension benefit into an annuity. This insulates retirees from risk in the equity and bond markets in the years between retirement and death.

only those summary statistics across investor styles. Each summary statistic has a distribution because of variation in macrodemographic and macroeconomic conditions. We derived those distributions by simulating a large number (500) of macro environments for each investor style. Our objective is thus to compare the distributions of, say, median DC pension benefits across investor styles, the 10th percentile of pension benefits across investor styles, et cetera.

Analysis

Table 3 presents summary statistics of the distribution of mean present values of DC pension benefits, for each of the seven investor Styles that we consider. For example, the average mean benefit under the GBF investor style was $286,000. Under adverse macro conditions, the mean was lower; under favorable conditions, it would be higher. The 10th percentile of the distribution of means was $211,000 and the interdecile range (difference between the 90th and the 10th percentiles) was $153,000.

Table 3: Summary Statistics over Macro Scenarios of the Mean DC Pension Benefit ($1,000s)

Investment Style	Mean	P10	P25	Median	Inter Decile Range
GBF	286	211	244	282	153
MMF+GBF	253	198	225	250	111
DEF+GBF	358	228	267	340	285
DEF	463	190	238	401	597
EIF	511	204	256	440	673
Conservative TDF	328	221	260	315	232
Aggressive TDF	390	222	263	363	371

Note: Each investor Style was simulated under 500 macro environments. For each of these macro scenarios, we calculated the mean present value of DC pension benefits. This table summarizes the distributions of mean benefits across macro scenarios. Also see Figure 3.

On average, mean benefits were lower for all-debt styles (GBF and MMF+GBF) than for all-equity styles (DEF and EIF). As expected, mixed debt and equity styles (DEF+GBF, conservative TDF, aggressive TDF) performed in between all-debt and all-equity styles.

While all-equity styles outperformed all-debt styles on average, their risk or volatility was greater, as demonstrated by their wider interdecile ranges. Indeed, all-equity styles do not stochastically dominate all-debt styles at the mean level of benefits. For example, at the 10th percentile, all-equity styles performed worse than the GBF style. The optimal investor style for the mean individual is therefore ambiguous; in most of the states of the world, an all-equity style such as EIF performed best, but individuals with a strong risk aversion may prefer an all-debt style such as GBF. "Heat map" tables below show how often the various investor styles outperform each other.

The appendix contains tables with summary statistics of the distributions of the 10th percentile, the 25th percentile, and the median of the present value of DC pension benefits, similar to Table 3 for the mean benefit.

Cumulative Distributions: The following figures show, for each investor Style, the cumulative distribution of the present value of DC pension benefits across macro scenarios. The first figure, Figure 3, shows the cumulative distribution of the mean benefit amount. For any investor Style the curve shows the fraction of the macro scenarios where the accumulated pension benefit was less than or equal to the value on the horizontal axis. For example, Equity Index Fund (the right-most or purple curve) investors earned mean benefits of around $440,000 or less in 50% of the macro scenarios. Investors in the Conservative TDF (the red curve) earned mean benefits of around $315,000 or less in 50% of the macro scenarios and investors in the MMF+GBF (the orange or left-most curve) earned mean benefits of around $250,000 or less in 50% of the macro scenarios.

The distributions of the mean benefit for TDFs are sandwiched between the all-equity funds and the all-debt funds. The constant-weighted debt and equity portfolio (DEF+GBF) falls between the two TDFs, representing an equity weighting that over the individuals' investing lifetime is less aggressive than the aggressive TDF and more aggressive than the conservative TDF.

Figures 4 to 6 below show the distributions of the 10^{th} percentile, the 25^{th} percentile, and the median of accumulated benefits. (Figure 3 corresponds to Table 3; Figures 4 to 6 correspond to the Appendix tables.) The same general patterns as for the means hold at these points in the distributions. For most macro scenarios, the ordering of the Styles is the same as for the means, with the equity Styles outperforming other asset allocations most of the time. Presumably because of its higher asset management fees (see Table 1), the DEF Style performed worse than the EIF Style. Also see Table 8 below.

Figure 3: Cumulative Distribution of Mean Pension Benefits by Investor Style

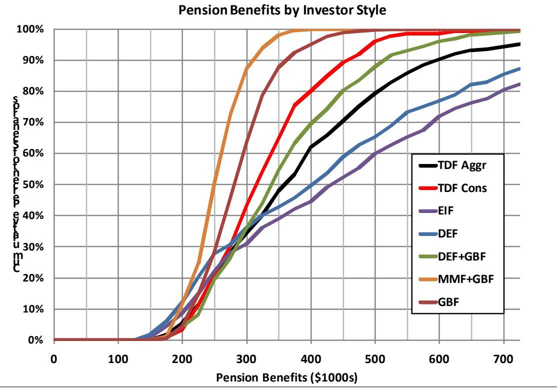
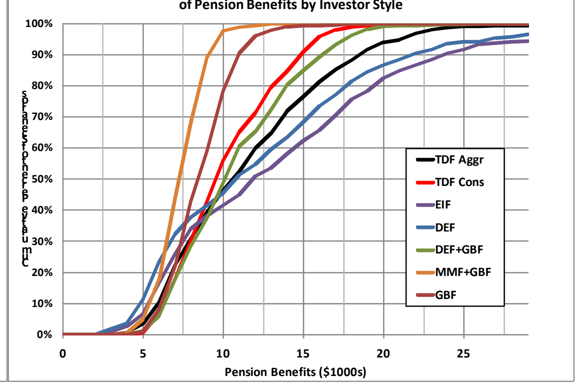
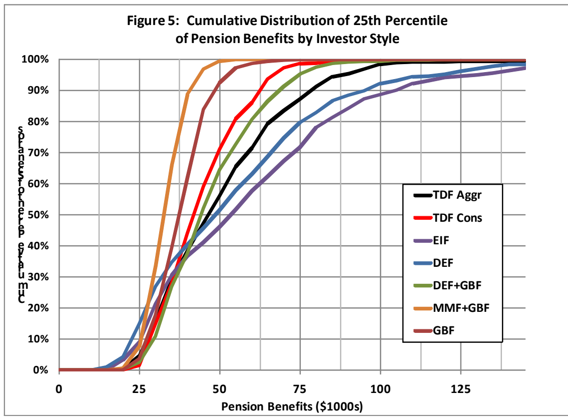
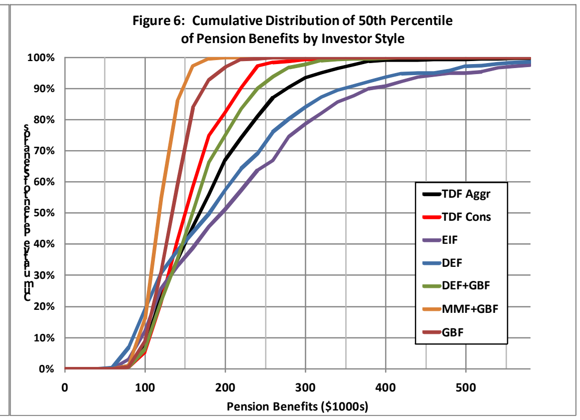


Figure 4: Cumulative Distribution of 10th Percentile of Pension Benefits by Investor Style







Dominating Styles: The final analysis compares pension benefits to determine which styles tended to outperform the others in a pair-wise "horse race." Each row of the "heat map" tables below represent the fraction of macro scenarios where the benefit to the investor Style in the left hand column (Investor Style A) exceeded the benefit to the investor Style in the columns to the right (Investor Style B). The data underlying Tables 4 to 7 are the same as those depicted in Figures 3 to 6; the "heat map" tables summarize how often the various Styles outperform one another, i.e., how often one curve lies to the right of another curve.

Consider Table 4 with a comparison of mean benefits across investment Styles. It reflects the same data as Figure 3 and Table 3. The color coding is such that green cells represent cases where Investor Style A had higher pension benefits in a large share of the macro scenarios compared to Investor Style B. Red cells represent comparisons in which Style A performed poorly relative to Style B, whereas no clear winner emerged in yellow cells. Rows with a predominance of green cells denote relatively high-performing investment styles. The mean GBF investor enjoyed higher benefits than the mean MMF+GBF investor in 97% of the macro scenarios and outperformed the mean DEF+GBF investor in 26% of scenarios. Notably, the TDFs frequently outperformed the debt-only funds, while equity Styles win large fractions across the board.

The next column in Table 4 shows the fraction of the macro scenarios where the mean Style A investor earned pension benefits greater than the mean of all other investors. The mean GBF investor beat all other mean investors in 24% of the macro scenarios, while the mean EIF investor beat all other mean investors in 73% of scenarios. The mean conservative TDF investor beat other mean investors in only 3% of macro scenarios.

The final set of columns in the table compares the benefits earned by the investor Style to an absolute threshold. All Styles earned a mean benefit of at least $100,000 in all macro scenarios and all Styles earned at least $200,000 in around 90% or more of macro scenarios.

Table 4: Comparison of Mean Pension Benefits across Investor Styles

	Percent of Scenarios Where Investor Style A Has a Larger Mean Pension Benefit than Investor Style B							Percent of Scenarios Where Investor Style A Has the Largest Mean Pension Benefit	Percent of Scenarios for Which Mean Pension Benefit is at least				
	Investor Style B												
Investor Style A	GBF	MMF+ GBF	DEF+ GBF	DEF	EIF	TDF Cons	TDF Aggr		$25,000	$50,000	$75,000	$100,000	$200,000
GBF		97%	26%	30%	26%	28%	27%	24%	100%	100%	100%	100%	96%
MMF+ GBF	3%		12%	24%	19%	4%	16%	0%	100%	100%	100%	100%	89%
DEF+ GBF	74%	88%		35%	25%	77%	30%	0%	100%	100%	100%	100%	96%
DEF	70%	76%	65%		0%	68%	63%	0%	100%	100%	100%	100%	88%
EIF	74%	81%	75%	100%		75%	76%	73%	100%	100%	100%	100%	91%
TDF Cons	72%	96%	23%	32%	25%		26%	3%	100%	100%	100%	100%	97%
TDF Aggr	73%	84%	70%	37%	24%	74%		0%	100%	100%	100%	100%	95%

Tables 5, 6, and 7 below present "heat maps" for the 10th percentile, 25th percentile, and median investors. They reflect the same underlying data as Figures 4 to 6, respectively. The patterns are largely similar to the mean investor results. Even at the lower end of the distribution, the bond-only funds earned much less than the funds with equities. See Table 6 for the 25th percentile investor: in only 8% of macro scenarios did the 25th percentile of GBF investors' benefit exceed $50,000. Similarly, in only 1% of macro scenarios did the 25th percentile of MMF+GBF investors' benefit exceed $50,000, while between 29% and 54% of the time, other investors earned at least $50,000 at the 25th percentile.

Table 5: Comparison of 10th Percentile of Pension Benefits across Investor Styles

	Percent of Scenarios Where Investor Style A Has a Larger Pension Benefit than Investor Style B at the 10th Percentile							Scenarios Where Investor Style A Has the Largest Pension Benefit at the 10th Percentile	Percent of Scenarios for Which Pension Benefit at the 10th Percentile is at least				
	Investor Style B												
Investor Style A	GBF	MMF+ GBF	DEF+ GBF	DEF	EIF	TDF Cons	TDF Aggr		$10,000	$25,000	$50,000	$75,000	$100,000
GBF		100%	26%	36%	29%	29%	29%	25%	22%	0%	0%	0%	0%
MMF+ GBF	0%		8%	29%	22%	7%	17%	0%	2%	0%	0%	0%	0%
DEF+ GBF	73%	92%		45%	31%	71%	38%	3%	52%	0%	0%	0%	0%
DEF	64%	70%	55%		0%	60%	51%	0%	55%	6%	0%	0%	0%
EIF	71%	78%	69%	100%		70%	71%	66%	59%	8%	0%	0%	0%
TDF Cons	71%	93%	28%	40%	30%		30%	6%	44%	0%	0%	0%	0%
TDF Aggr	71%	83%	62%	48%	29%	70%		0%	54%	1%	0%	0%	0%

Table 6: Comparison of 25th Percentile of Pension Benefits across Investor Styles

	Percent of Scenarios Where Investor Style A Has a Larger Pension Benefit than Investor Style B at the 25th Percentile							Percent of Scenarios Where Investor Style A Has the Largest Pension Benefit at the 25th Percentile	Percent of Scenarios for Which Pension Benefit at the 25th Percentile is at least				
	Investor Style B												
Investor Style A	GBF	MMF+ GBF	DEF+ GBF	DEF	EIF	TDF Cons	TDF Aggr		$10,000	$25,000	$50,000	$75,000	$100,000
GBF		99%	27%	35%	28%	29%	29%	24%	100%	96%	8%	0%	0%
MMF+ GBF	1%		10%	29%	22%	5%	17%	0%	100%	92%	1%	0%	0%
DEF+ GBF	73%	90%		43%	30%	71%	36%	2%	100%	98%	36%	5%	1%
DEF	65%	71%	57%		0%	62%	56%	0%	100%	85%	49%	20%	8%
EIF	72%	78%	70%	100%		71%	71%	68%	100%	91%	54%	28%	11%
TDF Cons	71%	94%	29%	38%	29%		29%	6%	100%	99%	29%	1%	0%
TDF Aggr	71%	83%	64%	44%	29%	71%		0%	100%	96%	44%	13%	2%

Table 7: Comparison of 50th Percentile of Pension Benefits across Investor Styles													
	Percent of Scenarios Where Investor Style A Has a Larger Pension Benefit than Investor Style B at the 50th Percentile							Percent of Scenarios Where Investor Style A Has the Largest Pension Benefit at the 50th Percentile	Percent of Scenarios for Which Pension Benefit at the 50th Percentile is at least				
	Investor Style B												
Investor Style A	GBF	MMF+ GBF	DEF+ GBF	DEF	EIF	TDF Cons	TDF Aggr		$25,000	$50,000	$75,000	$100,000	$200,000
GBF		98%	26%	33%	27%	29%	27%	25%	100%	100%	100%	91%	3%
MMF+ GBF	2%		12%	26%	21%	5%	18%	0%	100%	100%	99%	84%	0%
DEF+ GBF	74%	88%		39%	28%	75%	33%	1%	100%	100%	100%	94%	25%
DEF	67%	74%	61%		0%	65%	59%	0%	100%	100%	97%	81%	43%
EIF	73%	79%	72%	100%		73%	73%	70%	100%	100%	98%	88%	49%
TDF Cons	71%	95%	25%	35%	27%		27%	3%	100%	100%	100%	95%	18%
TDF Aggr	73%	82%	67%	41%	27%	73%		0%	100%	100%	100%	93%	33%

The final "heat map" table, Table 8 shows the fraction of macro scenarios where one investor Style dominated another Style on all four statistics: the mean, the 10th percentile, the 25th percentile and the median. This is suggestive of "stochastic dominance" and indicates the dominant Style generated larger benefits for investors located at many points along the (lower half of the) distribution of outcomes. The pair-wise comparison of Styles in Table 8 is similar to that for the median in Table 7, except that the winning fraction for dominant Styles was generally lower in Table 8 where Style A must beat the competing Style on all four measures. As before, equity styles dominated non-equity styles most of the time. Among the equity styles, EIF dominated DEF because of DEF's higher asset management fees.

Table 8: "Stochastic Dominance" of Investor Styles								
	Percent of Scenarios Where Investor Style A Has a Larger Pension Benefit than Investor Style B at the Mean and at the 10th, 25th and 50th Percentiles							Percent of Scenarios Where Investor Style A Has the Largest Pension Benefit at the Mean, 10th, 25th and 50th Percentiles
	Investor Style B							
Investor Style A	GBF	MMF+ GBF	DEF+ GBF	DEF	EIF	TDF Cons	TDF Aggr	
GBF		97%	23%	28%	24%	24%	24%	21%
MMF+GBF	0%		7%	22%	18%	2%	12%	0%
DEF+GBF	70%	86%		34%	24%	69%	27%	0%
DEF	62%	68%	53%		0%	59%	51%	0%
EIF	69%	76%	67%	100%		69%	69%	65%
TDF Cons	66%	90%	21%	32%	24%		25%	2%
TDF Aggr	68%	78%	59%	37%	23%	68%		0%

5. Conclusions

This research, like others in this area, has potential implications for public policy and optimal retirement saving behavior. Through the scenario analysis, we examined the impact of various asset allocations on the retirement wealth of individuals, paying particular attention to the role of TDFs. Gaining a better understanding of these issues has important implications for the well-being of retired workers. Our analyses are based on complex simulations of the lifecycle, employment, and financial outcomes for US workers and require many assumptions about decision-making and specification of parameter values. Furthermore, there is no one simple way to summarize the performance of an investment strategy when the outcome of that strategy depends on individuals' circumstances and choices and the forces exerted on them and their portfolios by the macro economy.

Subject to the caveats below, our analyses show the following results.

- The TDFs that we specified generally outperformed the specified debt-only investment Styles. In around 70% of the macro scenarios, the TDFs generated larger pension wealth for investors in the bottom half of the benefit distribution and for the mean investor. Conversely, in about 30% of future states of the world the long-term government bond fund outperformed the TDFs.

- The all-equity investment Styles that we specified outperformed TDFs, usually on the order of 60% to 80% of the macro scenarios, depending on the funds and percentiles examined. The finding that all-equity funds outperform TDFs is consistent with Poterba et al. (2005).[11]

These conclusions are based on projected differences in DC pension benefit accumulations generated under 500 macro scenarios; a different set of macro scenarios could produce different results. Additionally, these results are sensitive to the premium on equity returns over debt built into the model, which is assumed to be 2.0%. Many factors affect scenario results. A different equity premium could imply significantly different results. A lower equity premium—perhaps reflecting recent trends—would narrow the range between outcomes of debt and equity styles. As a result, TDFs would outperform debt-only styles less often and equity-only styles more often. For example, the conservative TDF style based on an equity premium of 1.0 percent would dominate the lower half of the returns distribution of a debt-only (GBF) style in 53 percent of the macro environments, compared with 66 percent at a 2.0 percent equity premium. The analogous figures for the conservative TDF versus an equity-only (EIF) style are 33 percent (at a 1.0 percent equity premium) and 24 percent (at a 2.0 percent equity premium). Such equity premium effects are consistent with those found in other studies.

To further investigate the benefits of TDFs, we explored TDFs' ability to insure against poor market returns just prior to retirement. We calculated the compounded rates of return on T-Bonds and on equities in the five years prior to our cohort's 65th birthday. We then selected scenarios with particularly poor equity returns or particularly large negative differences between equity and T-Bond returns during this time window. For scenarios with very poor equity returns just prior to age 65, the mean benefit for the conservative TDF outperformed most equity investment styles. For scenarios with a few years in which T-Bonds far outperformed equities, the GBF Style outperformed even the conservative TDF, but the conservative TDF did much better than the aggressive one. This suggests that the appeal of TDFs is heightened when poor equity returns occur just prior to retirement. This phenomenon deserves further attention.

Potential extensions to our work include, among others, a closer examination of the insurance properties of TDFs, as sketched above; a more complete assessment of the role of equity premiums; an account for risk preferences similar to the approach used by

[11] See also Schiller (2005) for a discussion of TDFs and equity performance.

Holmer (2009); and the incorporation of such other sources of retirement financing as social security benefits and housing wealth.

Disclaimer

The views, opinions, and/or findings contained in this report are those of the authors and should not be construed as an official Government position, policy or decision, unless so designated by other documentation.

Work for this report was performed in accordance with the Statement on Standards for Consulting Services issued by the American Institute of Certified Public Accountants ("AICPA"). Our services were provided under contract DOLJ08327415 from the U.S. Department of Labor.

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It should also be noted that we were requested by the DOL to use the PENSIM micro-simulation software for our research. The analysis performed and described herein relies upon the software and the data contained in and distributed with the software. Neither the software nor the data has been independently verified by Deloitte FAS. All outputs are based on certain assumptions and should not be used to predict future performance. Further:

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APPENDIX

This appendix contains tables with summary statistics of the distributions of the 10th percentiles of the present values of DC pension benefits (Table A.1), their 25th percentiles (Table A.2), and their medians (Table A.3). The tables correspond to text Figures 4, 5, and 6, respectively.

Table A.1: Summary Statistics over Macro Scenarios of the 10th Percentile of DC Pension Benefits ($1,000s)

Investment Style	Mean	P10	P25	Median	Inter Decile Range
GBF	9	6	7	9	5
MMF+GBF	7	6	6	7	4
DEF+GBF	11	6	8	10	10
DEF	12	5	6	11	17
EIF	14	6	7	12	18
Conservative TDF	10	6	8	10	9
Aggressive TDF	12	6	7	11	13

Note: Each investor Style was simulated under 500 macro environments. For each of these macro scenarios, we calculated the 10th percentile of present values of DC pension benefits. This table summarizes the distributions of those 10th percentiles across macro scenarios. Also see text Figure 4.

Table A.2: Summary Statistics over Macro Scenarios of the 25th Percentile of DC Pension Benefits ($1,000s)

Investment Style	Mean	P10	P25	Median	Inter Decile Range
GBF	38	28	32	38	20
MMF+GBF	33	26	29	32	14
DEF+GBF	47	30	34	44	39
DEF	55	23	29	49	72
EIF	60	26	32	54	79
Conservative TDF	44	29	34	42	34
Aggressive TDF	50	28	33	47	50

Note: Each investor Style was simulated under 500 macro environments. For each of these macro scenarios, we calculated the 25th percentile of present values of DC pension benefits. This table summarizes the distributions of those 25th percentiles across macro scenarios. Also see text Figure 5.

Table A3: Summary Statistics over Macro Scenarios of the Median DC Pension Benefit ($1,000s)

Investment Style	Mean	P10	P25	Median	Inter-Decile Range
GBF	136	102	115	133	70
MMF+GBF	119	94	105	118	52
DEF+GBF	168	108	124	160	132
DEF	205	89	110	181	257
EIF	225	96	119	197	285
Conservative TDF	156	105	124	148	115
Aggressive TDF	181	104	123	168	173

Note: Each investor Style was simulated under 500 macro environments. For each of these macro scenarios, we calculated the median present value of DC pension benefits. This table summarizes the distributions of median benefits across macro scenarios. Also see text Figure 6.

Acknowledgements:

We appreciate the comments and suggestions offered by Joseph Piacentini, Anja Decressin, Lynn Johnson, and Keith Bergstresser.

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