

**PERSONALIZED RETIREMENT ADVICE AND MANAGED ACCOUNTS:
WHO USES THEM AND HOW DOES ADVICE
AFFECT BEHAVIOR IN 401(k) PLANS?**

Julie Agnew*

CRR WP 2006-9

Released: March 2006

Draft Submitted: February 2006

Center for Retirement Research at Boston College
550 Fulton Hall
140 Commonwealth Ave.
Chestnut Hill, MA 02467
Tel: 617-552-1762 Fax: 617-552-1750
<http://www.bc.edu/crr>

* Julie Agnew is an Assistant Professor of Finance and Economics at the College of William and Mary. The research reported herein was performed, in part, pursuant to a grant from the U.S. Social Security Administration (SSA) funded as part of the Retirement Research Consortium. The findings and conclusions expressed are solely those of the authors and do not represent the views of SSA, any agency of the Federal Government, the College of William and Mary or Boston College. The author thanks Financial Engines and Hewitt Associates for supplying the data used in this study. In particular, I would like to thank Asma Emneina, Robert D'Onofrio, Matthew Todd, Yan Xu and Lori Lucas for their support in making this study possible. I greatly appreciate their assistance with the data collection and for answering the many questions that arose during the course of this project.

© 2006, by Julie Agnew. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

About the Center for Retirement Research

The *Center for Retirement Research at Boston College*, part of a consortium that includes a parallel centers at the University of Michigan and the National Bureau of Economic Research, was established in 1998 through a grant from the Social Security Administration. The goals of the Center are to promote research on retirement issues, to transmit new findings to the policy community and the public, to help train new scholars, and to broaden access to valuable data sources. Through these initiatives, the Center hopes to forge a strong link between the academic and policy communities around an issue of critical importance to the nation's future.

Center for Retirement Research at Boston College

550 Fulton Hall
140 Commonwealth Ave.
Chestnut Hill, MA 02467
phone: 617-552-1762 fax: 617-552-0191
e-mail: crr@bc.edu
<http://www.bc.edu/crr>

Affiliated Institutions:

American Enterprise Institute
The Brookings Institution
Center for Strategic and International Studies
Massachusetts Institute of Technology
Syracuse University
Urban Institute

Abstract

This paper investigates two methods for improving participants' asset allocations in their 401(k) plans: personalized online advice and managed account services. This paper uses a unique new dataset of individual-level administrative data from one 401(k) plan and recommendation data from an advice provider. Preliminary results suggest that online advice and the managed account service appeal to different populations. Managed accounts tend to be attractive to individuals across most demographic groups, while the online advice appeals more to higher salaried, full-time workers. In addition, individuals who show a predisposition to seek advice are more likely to use one of the methods than to do nothing. Finally, although a causal relationship cannot be determined, trading activity is higher for those using the online advice system compared to those who do nothing. Future research will investigate in more detail how portfolio allocations and trading are influenced by use of the two systems.

I. Introduction

Many 401(k) plan sponsors are concerned by the frequency of suboptimal asset allocation decisions made by participants in their 401(k) plans. An excellent example of a popular allocation that is suboptimal is the tendency for investors to over-invest in company stock. The concern over asset allocations is growing as plans featuring auto-enrollment increase and many auto-enrolled individuals anchor to the default investment choice.¹ Default investment choices tend to be very conservative, resulting in participant portfolios that are undiversified and unlikely to generate returns sufficient for a secure retirement. Setting more diversified defaults is one option for plan sponsors to improve allocations. However, many companies are concerned about liability issues related to defaulting participants into more risky investments. Another option for plan sponsors is to offer investment education classes that encourage savings and diversified investments. Previous research shows some success with these programs. However, other research shows a tendency for seminar participants to procrastinate and not follow through with the advice they are given. This paper studies two other methods for improving asset allocations: personalized asset allocation advice from a third party computer system and managed account services that allow the participant to hand over the management of their 401(k) portfolio to an outside party.²

The goal of this research is to address two questions. First, what type of individual takes advantage of these two new options? Second, how are asset allocations and trading behavior influenced? Data show that not all participants who are offered financial education or financial advice services use them. This becomes an issue if those opting out are those who have been identified in the literature as the most likely to make the least efficient decisions. The results of this study will determine whether these approaches reach the vulnerable populations. In addition, it may identify population subgroups that need more targeted financial assistance or encouragement to use the offered resources. This is the first paper to study the characteristics of individuals using online advice and managed account options compared to non-users. The paper presents the preliminary results of this study and focuses primarily on the first research question. Future research will investigate more fully the subsequent influence of these options on asset allocations and trading.³

¹ This tendency is referred to as the “default bias.”

² The *2005 Hewitt Trends and Experiences in 401(k) Plans Survey* reports that 8 percent of plans surveyed offer or plan to offer a managed account option in 2006.

³ This paper does not analyze the optimality of the portfolios recommended by the online system or implemented through Managed Accounts but rather focuses on what type of individuals seek this type of advice. Bodie (2002) discusses why investors should be careful where they seek investment advice.

Two explanations for suboptimal investment allocations are the participant's lack of financial knowledge or the influence of plan design. Concern over individuals' financial literacy and ability to make appropriate financial decisions is not new. Survey evidence suggests that many individuals lack basic financial knowledge. Since 1991, John Hancock Financial Services has published several Defined Contribution Surveys that aim to measure the financial knowledge of the respondents.

The results often have been troubling. In a very recent survey, respondents were asked their familiarity with various investment options. Despite their stated familiarity with a particular option, they often gave very incorrect answers to questions. For example, only eleven percent of those who stated that they were relatively familiar with money market funds knew that these funds were restricted to short term investments. Furthermore, eighty percent of the surveyed individuals did not know that the best time to transfer money into bond funds is when interest rates are expected to decrease.⁴

Finally, in spite of the well-publicized Enron debacle, respondents in the most recent survey continued to believe that company stock is less risky than a domestic, diversified stock fund.

Not surprisingly, this evidence is supported by findings in the academic literature that suggest that many individuals make inefficient or inappropriate allocation decisions.⁵ For example, Agnew (forthcoming) and Benartzi (2001) find that individuals tend to over-invest in company stock. This is an issue because investing in one stock, especially a security that is highly correlated with one's own human capital, is contrary to standard portfolio theory. Furthermore, Agnew (forthcoming) finds that blue collar and low salaried workers (the individuals who will rely the most on their 401(k) savings during retirement) are most likely to make this mistake. This is probably because salary is proxying for financial literacy and blue collar workers most likely have the least financial education.

Participants' desire for financial assistance is clear and may result from recognition of their financial illiteracy. In a recent John Hancock Financial Services Survey, over three-quarters of those surveyed stated that they would like expert investment advice. Close to the same proportion wanted an expert to "support and affirm their investment decision."⁶ However, the survey also found that less than

⁴ Please note that overall the respondents did consider themselves less familiar with bond investments. Also, new research by Lusardi and Mitchell (2005) studying older households finds low financial literacy rates using a simple three question exam. They also summarize other survey findings in their paper.

⁵ It is important to emphasize that not all the literature shows that individuals are making mistakes. Bodie and Crane (1997) analyze a unique 1996 survey of TIAA-CREF participants and find that their allocations are in line with recommendations made by expert practitioners. One reason for this finding could be that TIAA-CREF participants tend to be better educated and more experienced financially with self-directed accounts than the U.S. population. Bodie and Crane conclude that their behavior might be "point of reference" for the future behavior of individuals as the general population increases in education and financial experience.

⁶ John Hancock Financial Services, 8th Defined Contribution Plan Survey, p. 16.

half of individuals who are offered financial planning or investment advisory services by their employer actually use them.

The second explanation for suboptimal behavior is that individuals are influenced by plan design. Previous research demonstrates the clear influence of plan design and behavioral biases on savings and asset allocation decisions. For example, Benartzi (2001) and Liang and Weisbenner (2002) demonstrate that company stock allocations are higher in employees' discretionary contributions when the 401(k) plan's match is in company stock.⁷ This result is contrary to rationale expectations and suggests that participants may be investing in company stock because they view the match as an implicit endorsement from the company. Sethi-Iyengar, Huberman, and Jiang's (2004) paper suggests that the probability of participation falls as the number of investment choices increases, suggesting that individuals may be susceptible to choice overload.⁸ Finally, as mentioned earlier, some individuals succumb to what is called the default bias and anchor to conservative default allocations and savings rates (Choi, Laibson, Madrian and Metrick 2001).

As a result of concern over employees' financial literacy and as a means to overcome the negative influences of plan design, many companies have offered financial education counseling. Previous academic research has shown that these educational efforts on the part of plan sponsors can improve participation rates and contribution rates in 401(k) plans. This research has focused mainly on traditional educational efforts that include written communications about the company's retirement plans, information about the financial markets and/or financial education seminars. Clark and d'Ambrosio (2002) provide a brief summary of the previous literature. They conclude that the literature shows a positive impact of financial education on savings behavior. Likewise, Bernheim and Garrett (2003) find that employer-based retirement education strongly increases savings among low and moderate savers in 401(k) plans. Lusardi (2004) also finds financial education seminars can dramatically increase wealth for families with low education and at the bottom of the wealth distribution. However, Choi, Laibson, Madrian and Metrick (2004) and Clark and d'Ambrosio (2003) show that when the effectiveness of employer education is judged based on subsequent investment behavior and not on intentions following the seminar, the success is more limited.

⁷ Brown, Liang and Weisbenner (2004) examine why some employers match in company stock and the implications of a company stock match on employee retirement wealth.

⁸ It is important to note that plan design features can also have positive effects. Auto-enrollment plans (Madrian and Shea (2001)) and automatic savings plans (Thaler and Benartzi (2004)) have proven successful in overcoming procrastination by effectively increasing participation rates and savings levels, respectively. These latter studies demonstrate how thoughtful plan design can improve participant behavior. Mitchell, Utkus and Yang (2005) complete an extensive study of the impact of different plan design features on participant investment behavior.

This is one reason for the need for different approaches for improving asset allocations such as the two studied in this paper. The introduction of personalized portfolio advice has been supported by the Department of Labor Advisory Opinion 2001-09A (December 14, 2001) that “allows financial institutions to provide advice directly to retirement plan participants when the advice is based on computer programs and methodology of a third-party, independent advisor, thereby eliminating conflicts of interest”(Financial Engines, 2002). The personalized advice is based on each individual’s expressed financial goals, personal characteristics and modern financial theory.

There is one research paper that investigates the effectiveness of online services. Ameriks (2001) conducts a thorough analysis of the influence of a software guided system using a sample of TIAA-CREF participants in a retirement plan. He finds that the guidance sessions have “a significant, positive impact on the likelihood that participants will reallocate assets or begin directing contributions to recommended investment accounts that were not using prior to the guidance session.” While future analysis by this author will rely on some of the methodology developed in Ameriks’ study, this paper focuses on who uses the advice system and provides new analysis of the managed account service.

Furthermore, this analysis is a useful complement to Ameriks’ (2001) work because the sample of participants in our study is very different. TIAA-CREF participants tend to be better educated and more affluent than the general population. In contrast, the participants in this study tend to earn less than the general population. Therefore, it is worthwhile to examine whether the response to portfolio recommendations is similar. The lower income response to advice is also relevant to the Social Security debate. The President’s Commission on Social Security Reform was charged with designing personal retirement accounts and one implication of this charge is that these accounts should be targeted at lower paid workers (Cogan and Mitchell, 2003). One other important distinction between the two studies is that the portfolio recommendations in the Amerik’s (2001) study were given over the phone or in person, *not* online. This could also influence the response to recommendations.

The preliminary findings of this paper suggest that the online advice system and managed accounts service appeal to different populations. Managed accounts tend to be attractive to individuals across most demographic groups, including by sex, employment tenure and full-time/part-time status. While salary is related to the probability of being a managed accounts user, the effect of salary is less compared to its influence on the probability of being an online user. The online advice system appeals more to higher-salaried, full-time workers, and slightly more to males. It also appears that individuals

who show a predisposition to seek advice or help, proxied for by investment in lifestyle funds, are more likely to use both offerings.

II. Data

This analysis focuses on one 401(k) plan and spans two time periods. In the first time period, the participants have access to computer-generated portfolio advice online from Financial Engines. In the second time period, they may continue to receive portfolio advice online or have their accounts managed by Financial Engines. Financial Engines manages the accounts to be consistent with the recommendation the participant would have received using online advice. In order to study the effect of portfolio recommendations on subsequent asset allocations and on trading behavior, datasets from two separate companies were combined: Hewitt Associates, the 401(k) plan's administrator, and Financial Engines, a company specializing in portfolio allocation advice and managed account services. These data were carefully prepared by both data providers so that individual participants were made completely anonymous to the researcher. The data are from one company's 401(k) plan. The company is a large retail firm that employs many part-time and seasonal workers.

A. Description of the Hewitt Data

The data from Hewitt include both cross-sectional data as of January 1, 2004 and daily time series data over the period March 1, 2004 through March 1, 2005. Figure 1 at the end of this section provides a data timeline. The cross-sectional data include demographic information for each participant. These data include the participants' sex, age, salary, time enrolled in the 401(k) plan, their scheduled number of weekly hours and whether they are considered an "active" worker. In addition, these data include the accumulated dollar balances in each fund as of January 1, 2004 for each individual.

From the cross-sectional data, several new variables are generated for each individual. A part-time/full-time indicator variable is created. Individuals scheduled to work less than 40 hours are considered part-time employees and those working 40 hours are considered full-time employees. In addition, a beginning of the year total dollar balance across investments is calculated for each individual and a dummy variable is created to indicate whether the participant allocates a non-zero amount to at least one of the three lifestyle fund choices. This is done to determine how these type of investments might affect the probability of seeking portfolio allocation advice or opting for the managed account service.

In addition to the cross-sectional data, daily transfer and contribution information at the individual level is available from March 1, 2004 through March 1, 2005. This paper utilizes the transfer data which includes the date of the transfer and the dollar amounts shifted to and from each fund on the transfer day. Participants may make fund transfers daily. All transfers in a given day are made on the same day if they are requested prior to the market close. For the remainder of the paper, a transfer will be called a “trade.” The contribution information includes the date of the contribution and the dollar amounts contributed to each fund. From these data, the percent allocated to each fund can be calculated and changes in the allocation percentages from one contribution to the next can be flagged. These calculations will be completed for a follow up research project and incorporated into the analysis.

B. Description of the Financial Engines Data

In this plan, starting on February 1, 2002 individuals were given access to portfolio advice via the internet (hereafter “Online System”). This offering was enhanced on October 28, 2003 with the introduction of “Integrated Advice” which was designed to increase use by reaching participants when they are actively thinking about their retirement investments. In the Integrated Advice approach, participants accessing their 401(k) plan’s website are automatically given personalized advice and the option to redirect to the Financial Engines website for further advice.

A second approach designed to reach *all* participants regardless of their web access or interest in retirement investments was launched on September 17, 2004. On this date, most of the active participants in the plan were mailed an easy-to-read, one page personal evaluation that rated the optimality of their personal savings rate, as well as their portfolio allocations. The portfolio allocations were rated across two dimensions; risk/diversification and company stock holdings. Each dimension was assigned a color code: red (not optimal), yellow (warning) and green (optimal). These data include the color-coded savings and portfolio evaluations, and they will be used in future analysis. In addition to providing the participant’s portfolio evaluation, the letter included an offer to join the Managed Account service. If participants join the Managed Account service, then future trading and portfolio allocation decisions are initiated by Financial Engines based on that company’s in-house proprietary algorithms. The same algorithms are used for *both* the Managed Account service and the Online System.

The statement mailing permits us to divide the sample into two *nearly* equal time samples: pre-evaluation from March 1, 2004 to September 15, 2004 and post-evaluation from September 16, 2004 to

March 1, 2005. Purposefully, the pre-evaluation period ends a few days before the mailing in case participants access the system in anticipation of the mailing.

The Financial Engines data set includes a rich set of variables, including if and when individuals enrolled in the Online System and if and when they enrolled in the Managed Account service. Observations on every *participant-initiated* session on the Online System are included. In this study, sessions lasting over 1 minute are included as valid sessions and multiple sessions over one day are aggregated for each individual. Thus, if one participant accesses the system three times for 5 minutes each time, our data would consider this one session on that date lasting 15 minutes. This paper does not distinguish between a session that resulted from the participant being routed to the Financial Engines site from their 401(k) plan site via Integrated Advice, or from a participant who goes directly to the Financial Engines website. In addition to the time duration of each session, these data include the number of web page hits during the session. In future research, this variable may be included as a variable to proxy for how active the information search is during the session.

Recommendation information is also available in the Financial Engines data. Not all sessions result in a recommendation. However, if a recommendation is generated, then it is saved in a recommendation file that includes the date of the recommendation and the recommended 401(k) fund asset allocations for the participant's 401(k) plan. During one session, an individual may ask for and receive several recommendations. Financial Engines has suggested that the last recommendation made in a day be considered the official recommendation; the other recommendations within the day are deleted.

C. Constructing the Final Combined Sample

The Hewitt data do not include a variable that indicates whether an individual is an active participant in the 401(k) plan. Therefore, we constructed a rough measure for an active 401(k) plan participant. First, the employee must be considered an "active" worker. This accounts for 274,027 of the employees in the database. Not all of these "active" workers meet the 401(k) plan eligibility requirements. To be considered an active 401(k) participant, they must be eligible and also have either a balance as of January 1, 2004 *OR* make a contribution during the study time period (March 1, 2004 to March 1, 2005). This amounts to 101,467 401(k) participants.⁹

⁹ Plan administrators often only consider individuals making contributions in the year as active 401(k) participants. Future analysis will repeat the analysis for this subsample.

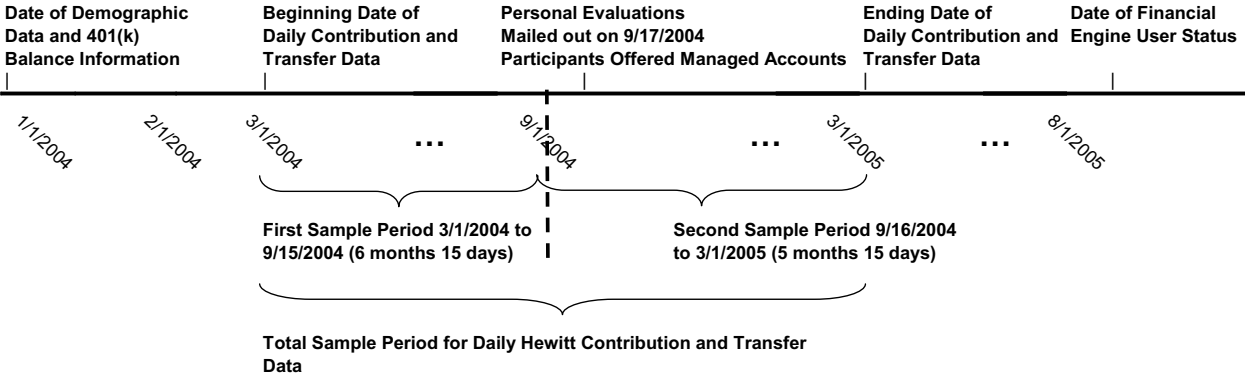
This “active 401(k) participant” sample is further restricted to participants who were sent a September evaluation letter from Financial Engines. The color coded evaluations are not available to individuals not receiving the letter. This brings the sample size to 82,923. Individuals may not have received letters because either Financial Engines did not have valid salary or mailing information for the individual in their database or because they were terminated prior to the mailing.

Next we wanted to restrict consideration to employees who were defined as active 401(k) participants during the time period. (Future analysis will examine whether terminated employees have different behavior than active employees.) Therefore, several additional Financial Engines variables are used to refine the sample to a group that was actively employed over the year studied. In the evaluation letters sent to the 82,923 sample, 7,426 individuals were not given savings advice because Financial Engines considered them “ineligible.” These individuals were dropped from the sample because of their ineligibility to contribute. In addition, the Financial Engines data include a variable that indicates whether the individual is an active employee or terminated as of August 2005. 8,262 of the remaining sample were considered terminated as of this date. The actual termination date is not available so it is impossible to determine whether these participants left before March 1, 2005 or after. Therefore, it is possible that, by dropping this sample, some of the individuals leaving *after* the sample time period may be deleted. However, this seemed the most reasonable way to attempt to eliminate the individuals that leave during the sample time period. This brings the sample size to 67,235.

The sample was reduced further if salary information was missing (3,744 were eliminated) or for what appeared to be data errors (106 were eliminated). This resulted in a final sample size of 63,385 participants.

Figure 1 provides a data timeline and details the two sample time periods.

Figure 1. Data Timeline



III. Demographic and Employment Characteristics of the Sample

Table 1 provides basic demographic details of the participant sample. There is a large number of part-time employees accounting for over half (59 percent) of the sample. Individuals employed by this firm are primarily female (82 percent). There are more males employed full-time than part-time, but the reverse is true for females. The average salary is \$23,464. When broken down by whether employees are part-time or full-time (hereafter “employee status”), the mean salaries of full-time employees are substantially higher than part-time employees (\$35,162 vs. \$15,370). The average number of years for an employee at the firm is 11.41 years. Since this is based on the original hire date, it is possible that the employee had some breaks in employment during this period. Full-time employees have a slightly higher tenure than part-time employees (12.71 years versus 10.51 years). The average age is approximately 46 years for employees and does not vary much across employment status. Finally, the average account balance is highly variable with an average amount of \$23,927. This variability is caused by a few participants with very large balances (greater than \$500,000). Not surprisingly, full-time employees have larger balances than part-time employees.

It is also interesting to examine the frequency of 401(k) participants across different demographic ranges, including salary, employment years, age and 401(k) balances. This breakdown is found in Table 2. As one would expect, the salaries are clustered in the low salary ranges due to the large percentage of part-time workers. Fifty-five percent of the sample earns less than \$20,000, and 27 percent of participants earn from \$20,000 to \$30,000. Only three percent of the employees earn over \$80,000.

In 10 percent of the sample, employment is less than two years. The two most frequent employment ranges are two to five years (21 percent of the sample) and five to ten years (24 percent of the sample). Nineteen percent of the sample have more than 20 years of employment.

More than half of the sample covers the ages of 40 to 60 years old. Only 5 percent in the sample are over 65 and 8 percent are under 25. Finally, over half (58 percent) of participants have 401(k) balances under \$10,000.

IV. Who Uses the Online System or the Managed Account Option?: Summary Statistics

A. Sample Period 1 (Pre-Evaluation): March 1, 2004 to September 15, 2004- Only the Advice System Offered

Table 3 presents statistics and frequency data related to the first sample time period (March 1, 2004 to September 15, 2004) when participants had only the advice system as an option. The participants are divided into two main groups: Non-Users and Online Users. The Online Users are then divided into three subgroups: those who access the advice system once over the time period, those who access the advice system more than once over the time period and those who are enrolled in the advice system but do not access the system over the time period.

Fifteen percent of the participants are enrolled in the advice system. Interestingly, there appear to be large demographic differences between the Non-Users and the Online Users. Non-Users average a much lower salary (\$20,021) than Online Users (\$42,426). This may be driven by the fact that a higher percentage of full-time workers take advantage of the system (68 percent of Online Users work full-time) than choose not to (36 percent of Non-Users work full-time). Full-time workers earn higher salaries on average. The average number of years employed is higher for Online Users (16.21 years) compared to Non-Users (10.54 years). Finally, the average 401(k) balances are much larger for Online Users (\$61,727 versus \$17,064).

Table 3, Panel B reports the average number of trades and distribution of trades across groups. Recall that a trade refers to a 401(k) fund transfer in this study. It is important to note that the results from the current analysis cannot be used to determine causality between the group type and trading. For example, it is possible that individuals with a predisposition to trade are also more likely to be Online Users. That being said, the results presented in Panel B suggest that a closer look into the causality of the trades is warranted because Online Users on average trade more than Non-Users (1.03 times vs .13 times over sample period 1). Interestingly, when the approximate annual number of trades ($.13 * 2 = .26$) for Non-Users is calculated, it is roughly equal to the annual number of trades found in the Agnew, Balduzzi and Sundén (2003) study (.26) of nearly 7,000 retirement accounts over the April 1994 to August 1998 time period and the average annual trades found in the Mitchell, Mottola, Utkus and Yamaguchi (2005) study (.30) of 1.2 million workers in 1,500 plans over the 2003-2004 time period. This infrequent trading is also consistent with Ameriks and Zeldes (2004).

Within the Online Users subgroups, the more frequently the participants access the advice system, the higher the average number of trades. For example, those who access the advice system more than once, trade on average 1.92 times over the six month time period, compared to a trading average of .69 times for those who have enrolled but did not access the system. Looking at the frequency of trading, 94 percent of Non-Users do not trade over the sample time period. This compares to 65 percent of Online Users. Consistent with the average trade findings, the lowest frequency (41 percent) of zero trades is calculated for the users who access the system multiple times. These users also show a higher frequency of trading more than one time, relative to other groups.

Future research will examine the trading in more detail using methodology based on Ameriks' (2001) study. The analysis will compare the time of the trade to the date that a Financial Engines recommendation is received. In addition, the analysis will study the extent to which the change in the asset allocation relates to the recommendation made. Particular attention will be paid to how company stock holdings and the default allocations of auto-enrolled participants are influenced.

B. Sample Period 2 (Post – Evaluation): September 16, 2004 – March 1, 2005: Advice System and Managed Account Options Offered

After the evaluation mailings in September 2004, individuals were given two options: the original option to use the Online System and a new option to join the Managed Account program. As a result, at the end of the period, individuals can be broken down into four groups: “Managed Account Users,” “Non-Users,” “Online Users,” and those who joined and then subsequently dropped the Managed Account System, “Dropped Managed Account.” These data do not have any information regarding whether or not the dropped users became Online Users.

Each individual now has a pre-evaluation grouping and a post-evaluation grouping. Table 4 relates the pre-evaluation grouping to the post-evaluation grouping and produces some interesting findings. First, 18 percent of the participants who were Online Users during the first sample time period transitioned to Managed Accounts. Only a small percent joined Managed Accounts and then subsequently dropped the service (3.52 percent). The majority (78 percent) remained Online Users.

Of the pre-evaluation Non-User grouping, 9.22 percent joined the Managed Account System compared to .95 percent who joined the Online System. Although 9.22 percent is less than the 18 percent of pre-evaluation Online Users who joined the Managed Account System, in total numbers of participants it is much larger (4,947 versus 1,765 participants). In fact, this number of participants is

equal to approximately half of the total Online Users in the pre-evaluation period. This suggests that the Managed Account service may be very appealing to a *new* subset of participants who were not interested in the Online System. These individuals may prefer to be passive about their finances while the Online Users may prefer to stay in control. By March 1, 2005, 24 percent of the sample was using either Managed Accounts (13 percent) or the Online System (11 percent). Only one percent of the sample dropped out of Managed Accounts.

It is important to note that all individuals were given a three month *free* trial period from the time they enrolled in Managed Accounts.¹⁰ Some might argue that this inflates the enrollment. However, of those considered Managed Account Users as of March 1, 2005, 96 percent had been enrolled longer than the free trial period. The remainder of the individuals in the sample joined the system during the three months prior to March 1, 2005 and were still in the free trial period. The enrollment date of the one percent who dropped out is not available so it is not possible to determine if the time they left the plan related to the date their free enrollment ended.

Table 5, Panel A is similar to Table 3, Panel A and examines the average demographic characteristics of post-evaluation groupings. The results lend some further support to the hypothesis that Managed Accounts may be appealing to a different type of individual. As in Table 3, the Online Users report higher average salaries than the Non-Users (\$41,007 compared to \$19,583). They also have higher 401(k) balances (\$57,471 versus \$15,934) are employed longer (15 versus 10 years) and the percentage of full-time employees is higher for Online Users than for Non-Users (66 percent versus 36 percent). The average age of both groups is 45 years old.

In contrast to the Online Users, part-time employees make up a majority (54 percent) of the Managed Account Users. The Managed Account users also have lower average salary compared to the Online Users (\$27,766 versus \$41,007) and are older (49 years old compared to 45 years old). The 401(k) balances are also smaller (\$33,776 versus \$57,471). This suggests that this new service is more appealing to part-time employees and those who are earning less money. Relative to the Non-User, the salary, balances and age are higher for the Managed Account users. However, the statistics resemble Non-Users more than the Users.

Table 5, Panel B focuses solely on the groups that can self-initiate trades. The Managed Account Users' trades are initiated by Financial Engines and are therefore excluded. Also, it cannot be

¹⁰ In general, Financial Engines charges an asset-based fee to its clients which is deducted monthly or quarterly from the account of the plan participant. The Financial Engines website reports that fees are comparable to those associated with life-cycle mutual funds and are typically 60 basis points or less (source: www.financialengines.com)

determined when the individual dropped the Managed Account system and thus whether the trades were initiated by Financial Engines or the participant, therefore statistics are not calculated for the “Dropped Managed Account” category. Therefore, the two post-evaluation groupings of interest are the Non-Users and the Online Users.

Once again, the Online Users on average trade more (.86 times versus .11 times over time sample period 2). In addition, 95 percent of the Non-Users never trade over the time period compared to 70 percent of the Online Users. Once again, future analysis will attempt to determine if the trading is following a recommendation and how well that trade relates to the suggested allocations.

The mean statistics reported for the pre-evaluation and post-evaluation groupings suggest that participants’ choice of options may be related to demographic characteristics. The following analysis will focus on the post-evaluation groupings. Charts 1 through 6 examine the percentage of each demographic range reported in Table 2 that participates in each post-evaluation grouping. The footnotes report the sample size of each demographic group. This information is also available in Table 2.

Chart 1 considers sex. A lower percentage of males (65 percent) are Non-Users compared to females (78 percent). The percentage of females using Managed Accounts (10 percent) is roughly the same as the percentage using the Online System (11 percent). On the contrary, the percentage of males using the Online System (23 percent) is over double the percentage of males using Managed Accounts (11 percent). Furthermore, there does not appear to be a sex difference among Managed Account Users. Nearly the same percentage of each sex group is reported (females-10 percent, males-11 percent). On the other hand, the percentage of males using the Online System (23 percent) is double the percentage of females (11 percent) using it. It is possible that because the advice is given online that it favors males. Choi, Laibson and Metrick’s (2002) study of the effect of online trading availability on the trading behavior of individuals in 401(k) plans found that males were more likely to use online trading in 401(k) plans than females. Their results also found young and wealthy individuals were more likely early adopters. Looking at a very different sample of discount brokerage investors trading in non-401(k) accounts, Barber and Odean (2002) found similar results. They found that individuals switching to online trading were more likely young men with high incomes. Finally, a recent study by Mitchell, Mottola, Utkus and Yamaguchi (2005) found traders in general tend to be affluent, older men. Their study uses a comprehensive database of 1.2 million workers participating in 401(k) plans. This group of traders also tended to use the internet for 401(k) account access.

Chart 2 examines employment status. Not surprisingly based on earlier statistics, full-time employees have a lower percentage of employees not taking advantage of the options (66 percent versus 82 percent). As with the sex results, there is not much difference between the Managed Account Users based on employment status (10 percent – part-time, 12 percent – full-time). However, full-time employees have a larger percentage of participants using the Online System than part-time employees (7 percent- part-time, 21 percent – full-time).

Chart 3 examines salary categories. The percent of participants not using either system monotonically declines with salary. Eighty-five percent of those earning less than \$20,000 are Non-Users compared to 27 percent of those earning more than \$80,000. The Managed Account Users show an increase with salary, from under \$20,000 (9 percent) to \$40,000-\$50,000 (15 percent). It then increases at a much slower rate for the remainder of the salary categories. This is further evidence suggesting that the Managed Account system appeals to individuals across demographic categories and ranges.

A sharp increase in the percentage of individuals using the Online System is found as the salary ranges increase. Only five percent of those earning under \$20,000 use the Online System compared to half of those earning over \$80,000. This positive relationship between salary and online use is consistent with findings from Choi, Laibson and Metrick (2002) and Barber and Odean's (2002) studies examining online trading.

Chart 4 addresses the years employed. There is also a decrease in the percentage of Non-Users as the time employed increases. Eighty-eight percent of employees employed under 2 years are Non-Users compared to 63 percent of those working 40-50 years. Tenure appears positively related to both Managed Account and Online System use. Managed Account (Online System) users report 6 percent (6 percent) of those with less than two years of employment using the system versus 15 percent (28 percent) of those employed 30-40 years.

Chart 5 considers the employee's age. There appears to be a non-monotone effect of age. For example, 91 percent of those under 25 years old are non-users compared to a low of 71 percent for 50 to 60 years old. The percentage then increases again to 85 percent for those over 65 years old.

Chart 6 shows the relationship of participation in each category to 401(k) balances. As mentioned earlier, one would expect individuals with larger balances to spend more time and effort managing their accounts and this bears true. For those with less than \$1,000 balances, 90 percent are Non-Users. This compares to 38 percent of those with balances greater than \$100,000. Once again, the

Online Users demonstrate a marked increase in the percent of the balance ranges using this option. For those with balances less than \$1,000, only five percent of the individuals use the system compared to 41 percent of those with balances over \$100,000. As with the salary findings, the Managed Account percentages seem to increase at a slower rate beginning with accumulated 401(k) balances greater than \$10,000.

V. Who Uses the Online System or the Managed Account Option?: An Econometric Analysis

The charts and tables presented in Section III suggest that demographic characteristics do relate to the decision to use the Online System or the Managed Account service. The non-parametric results suggest that the Online System is appealing to high salaried, full-time employees with large balances. Conversely, the Managed Account System appeals more evenly to demographic types across the board and lower salaried employees relative to the Online Users. Given that the participants' four choices at the end of the sample period (March 1, 2005) are non-ordered, a Multinomial Logit Regression is used to study this decision.¹¹ A thorough description of this model can be found in Greene (1993) and Long and Freese (2001). This section will describe the results of this analysis.

Table 6 reports the marginal effects for each continuous independent variable (Df/dx) calculated at their means and changes of one standard deviation centered at the means. Discrete changes from 0 to 1 are reported for the binary variables. Robust standard errors are calculated and significant variables at the five percent (one percent) level are denoted by a * (**). The regression is estimated over two samples. Panel A reports the regression for the entire sample. Panel B reports the regression including a new variable that indicates whether the participant has invested any of his/her 401(k) balance (as of January 1, 2004) in lifestyle funds. Approximately 4,378 individuals did not have a balance as of January 1, 2004, so these participants were dropped from the regression.

Table 6, Panel A shows that the average full-time employee is nearly 4 percent more likely to use the Online System than a part-time employee and 4 percent less likely to be a Non-User. The discrete effect of full-time status on the probability of joining the Managed Account Service is much smaller and insignificant. The effect of full-time status for those dropping the Managed Account Service is significant but economically small. Thus, it does appear that the Managed Account service appeals to

¹¹ The four choices are the choice not to participate, the choice to enroll in Managed Accounts, the choice to drop Managed Accounts, and the choice to use the Advice System.

both full-time and part-time employees, while the Online Service is most appealing to full-time employees.

Sex effects are significant for every choice but the Non-User. However, the effects are very small. The largest effect is for Online Users and it is only a one percent increase.

Salary has a large impact on choosing the Online System. A one standard deviation increase in salary centered at the mean increases the probability of using the Online System for an average user by 5.5 percent. The effect is two percent smaller but still significant for the Managed Account Users- a 3.5 percent increase. A similar increase in salary for an average participant decreases the probability of being a Non-User by 9.5 percent.

Focusing exclusively on tenure, years employed at the firm has the largest positive effect on the choice to become an Online User with a one standard deviation increase in years employed resulting in a 2.6 percent increase in participation. The effect is smaller for Managed Account Users with a less than 1 percent increase for a 1 standard deviation change. The probability of being a Non-User decreases by 3.5 percent with a one standard deviation increase in tenure.

Interestingly, age has a positive impact on Managed Account Users, increasing the probability of being a user by 2.9 percent with a one standard deviation increase. On the other hand, it decreases the probability for an average individual to be an online advice user by 2.2 percent. The effect is negative but smaller for the Non-Users.

Finally, while significant, the effect of 401(k) balances is only economically meaningful for the Non-Users where a standard deviation increase in balance decreases the probability of being a Non-User by 1.7 percent.

Panel B repeats the analysis for a smaller sample of participants with reported balance and allocation information as of January 1, 2004. A dummy variable is included if any of the 401(k) balance is invested in what are called lifestyle funds. These funds are professionally managed funds that invest in stocks, bonds, and cash. In this plan, three funds are offered and they are designed to fit individual levels of risk tolerance. The funds were designed so that investors would invest 100 percent of their 401(k) assets in *ONE* lifestyle fund. However, there are no restrictions on an individual asset allocation in this plan and most of the lifestyle investors do not put all of their balances in one lifestyle fund. In this sample, 34 percent of participants invest in at least one lifestyle fund. Of that group, 47 percent invest in more than one lifestyle fund. This misuse is consistent with findings from a larger study of multiple Hewitt 401(k) plans covering over 1 million participants (Hewitt, 2005b). This study found 39.3 percent

of individuals invested in lifestyle funds when they were available in 2004. They found only 15 percent had all of their non-company stock balances in a single lifestyle fund. In this plan, less than 1 percent have their entire balance in one lifestyle fund.¹² This variable is included because an individual's decision to invest in a lifestyle fund may indicate he is seeking professional assistance with his 401(k) allocations. Therefore, such individuals may be more likely to want to use Online Advice or Managed Accounts. These preliminary results support this. However, care must be taken when interpreting these results and more work is needed to confirm the results. This is because it is possible that some of the individuals using Online Advice are investing in lifestyle funds because Financial Engines recommended this investment. Therefore, future analysis will examine the recommendations to determine whether this is a factor. It is important to keep this caveat in mind when considering these results.

The results show that the probability of being a Managed Account User or an Online User substantially increases if the participant invests in lifestyle funds. The probability of being a Managed Account user increases by 6.8 percent for the average individual when his 2004 balance is invested in a lifestyle fund. Similarly, the probability increases by 7.5 percent that the individual is an Online User and decreases the probability of being a Non-User by 14.9 percent.

Interestingly, after including the investment dummy, sex and employment tenure are no longer significant for the Managed Account decision. These variables were significant in the earlier regression but very small. Only salary and age have a significant *and* economically meaningful impact. In contrast, *all* the demographic variables remain significant for the Online Users after the inclusion of the investment dummy.

In summary, the regression analysis findings largely support the results from the non-parametric analysis.

V. Preliminary Conclusions and Plans for Future Research

From these preliminary findings, it appears that individual characteristics are more predictive of Online Users than Managed Account Users. This suggests that the Managed Account option appeals more broadly across demographic groups and employment variables, including sex, full-time/part-time status, and employment tenure. On the other hand, the Online System appeals more to full-time

¹² This is most likely because the company match was in company stock. Since participants are infrequent traders in this plan, they probably did not trade out of their company stock holdings to invest all of their assets in the lifestyle fund. This will be verified in future research.

employees and higher salaried employees relative to Managed Account users. Finally, both systems appear to interest employees who already show a predisposition for advice or portfolio assistance, proxied for by their investment in lifestyle funds. This is an interesting finding because studying participants' asset allocations may help plan sponsors identify "reluctant" investors who are not predisposed for assistance and may need targeted encouragement to use offered resources. In addition, these results suggest that further examination of the lowest salaried participants is still needed.

The preliminary results raise some interesting questions for future research. The author's plan is to focus on the Online Users and the effect of recommendations on asset allocation and trading. Both transfers *and* contribution changes will be studied. Similar to Ameriks (2001), the planned analysis will include a study of the relationship between the time a recommendation is received and when transfers and contribution changes are made. The analysis will also study whether the trades result in portfolio allocations similar to the recommendations. Careful attention will be paid to the effect on company stock holdings and holdings invested entirely in the default allocation as a result of auto-enrollment.¹³

In addition, future analysis will take more full advantage of variables and observations included in the dataset. For example, some individuals report their assets outside of their 401(k) plans and observations are available for terminated employees. Given approval from the plan sponsor, a survey of participants from the different categories could yield interesting results regarding how attitudes towards savings and finance, time constraints, and financial literacy relate to their decision to use Managed Accounts or Online Advice. Already, there is preliminary evidence based on a sample of older households from Lusardi and Mitchell (2005) suggesting an association between retirement planning tools used and financial literacy.¹⁴

Finally, an examination of the Online Users information search and its relationship to their subsequent portfolio allocations and trading could be interesting. The extent of the information search can be roughly approximated by the number of sessions and the time duration of the online sessions. In addition, the number of recommendations they receive for each session can also be used as a measure. Furthermore, if a survey is completed, individuals' financial literacy can be related to their information search.

¹³ Auto-enrollment was introduced on 9/15/97 for new hires only. Originally, the default contribution rate was three percent after tax. Starting in 1/1/2005, the default contribution is four percent before tax.

¹⁴ Planning tools in their analysis included talking to family/friends, talking to coworkers/friends, attending a retirement seminar, using a calculator/worksheet and consulting a financial planner.

The future study should help paint a more complete picture of who uses personalized advice systems and managed account services and how it affects their subsequent behavior. From the results, recommendations can be made to plan sponsors regarding whether certain populations need more targeted attention and judgments can be made of how successful these systems are in correcting common portfolio allocation mistakes, such as over-investment in company stock and default option bias.

References

- Agnew, Julie. "Do Behavioral Biases Vary Across Individuals?: Evidence from Individual Level 401(k) Data." Forthcoming in the *Journal of Financial and Quantitative Analysis*.
- Agnew, Julie, Pierluigi Balduzzi and Annika Sunden. 2003. "Portfolio Choice and Trading in a Large 401(k) Plan." *The American Economic Review*, 93(1), 193-215.
- Ameriks, John and Stephen P. Zeldes. 2004. "How Do Household Portfolio Shares Vary with Age." Working Paper, Columbia Business School
- Ameriks, John. 2001. "The Response of TIAA-CREF Participants to Software-driven Asset Allocation Guidance." TIAA-CREF Working Paper 3-080101.
- Barber, Brad M. and Terrance Odean. 2002. "Online Investors: Do the Slow Die First?" *The Review of Financial Studies*, 15 (2), 455-487.
- Benartzi, Shlomo. 2001. "Excessive Extrapolation and the Allocation of 401(k) Accounts to Company Stock." *The Journal of Finance*, 56 (5), 1747-1764.
- Bernheim, B. Douglas and Garrett, Daniel M. 2003. "The Effects of Financial Education in the Workplace: Evidence from a Survey of Households." *Journal of Public Economics* 87, 1487-1519.
- Bodie, Zvi and Dwight B. Crane. 1997. "Personal Investing: Advice, Theory and Evidence." *Financial Analysts Journal* 53 (6), 13-23.
- Bodie, Zvi. 2002. "An Analysis of Investment Advice to Retirement Plan Participants." Pension Research Council, Working Paper 2002-15.
- Brown, Jeffrey R., Nellie Liang and Scott Weisbenner. 2004. "401(k) Matching Contributions in Company Stock: Costs and Benefits for Firms and Workers" National Bureau of Economic Research Working Paper 10419.
- Choi, James J, David Laibson, Brigitte C. Madrian and Andrew Metrick. 2004. "Saving for Retirement on the Path of Least Resistance." Working Paper.
- Choi, James J, David Laibson, Brigitte C. Madrian and Andrew Metrick, 2001, "For Better or For Worse: Default Effects and 401(k) Savings Behavior." NBER Working Paper No. 8651.
- Choi, James J, David Laibson, and Andrew Metrick. 2002. "How Does the Internet Affect Trading? Evidence from Investor Behavior in 401(k) Plans." *Journal of Financial Economics* 64 (3), 397-421.

- Clark, Robert L. and Madeleine B. d'Ambrosio. 2002. "Financial Education and Retirement Savings." Conference Proceedings from the Retirement Implications of Demographic and Family Change Symposium (June).
- Clark, Robert L. and Madeleine B. d'Ambrosio. 2003. "Ignorance is Not Bliss: The Importance of Financial Education." TIAA-CREF Research Dialogue Issue 78.
- Clark, Robert L. and Sylvester Schieber. 1998. "Factors Affecting Participation Rates and Contribution Levels in 401(k) Plans," *Living with Defined Contribution Plans*, Edited by Olivia S. Mitchell and Sylvester Schieber, University of Pennsylvania Press, pp. 38-68.
- Cogan, John F. and Olivia S. Mitchell. 2003. "Perspectives from the President's Commission on Social Security Reform," *Journal of Economic Perspectives*, Vol. 17 (2), pp. 149-172.
- Financial Engines. June 10, 2002. "CitiStreet to Take Fiduciary Responsibility and Provide First Fully Integrated, Un-Biased Advice to Retirement Plan Participants, Powered by Financial Engines." Financial Engines Website (www.financialengines.com).
- Greene, W. H. *Econometric Analysis*, Prentice-Hall, Inc. Upper Saddle River, New Jersey (1997).
- Hewitt, Hewitt Trends and Experiences in 401(k) Plans Survey, 2005.
- Hewitt, 2005 Hewitt Universe Benchmarks- How Well Are Employees Saving and Investing in 401(k) Plans, 2005 b.
- John Hancock Financial Services, Eighth Defined Contribution Plan Survey.
- John Hancock Financial Services, Seventh Defined Contribution Plan Survey.
- Liang, Nellie, and Scott Weisbenner. 2002. "Investor Behavior and Purchase of Company Stock in 401(k) Plans- The Importance of Plan Design." Board of Governors of the Federal Reserve System Working Paper (2002).
- Long, J. Scott and Jeremy Freese. 2001. "Regression Models for Categorical Dependent Variables Using Stata." Stata Press, College Station, Texas.
- Lusardi, Annamaria. 2004. "Savings and the Effectiveness of Financial Education." *Pension Design and Structure: New Lessons From Behavioral Finance*, Edited by Olivia S. Mitchell and Stephen P. Utkus, Oxford University Press, pp.157-184.
- Lusardi, Annamaria and Olivia S. Mitchell. 2005. "Financial Literacy and Planning: Implications for Retirement Wellbeing." Pension Research Council Working Paper, PRC WP 2006-1, The Wharton School.

- Madrian, Brigitte C. and Dennis F. Shea. 2001. "The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior." *The Quarterly Journal of Economics*, Vol. CXVI, Issue 4, pp. 1149-1187.
- Mitchell, Olivia S., Gary R. Mottola, Stephen P. Utkus and Takeshi Yamaguchi. 2005. "The Inattentive Participant: Portfolio Trading Behavior in 401(k) Plans." Pension Research Council Working Paper, PRC WP 2006-2, The Wharton School.
- Mitchell, Olivia S., Stephen P. Utkus, and Tongxuan (Stella) Yang. 2005. "Turning Workers into Savers? Incentives, Liquidity, and Choice in 401(k) Plan Design." NBER Working Paper No. 11726.
- Sethi-Iyengar, Sheena, Gur Huberman and Wei Jiang. 2004. "How Much Choice is Too Much? Contributions to 401(k) Retirement Plans." *Pension Design and Structure: New Lessons From Behavioral Finance*, Edited by Olivia S. Mitchell and Stephen P. Utkus, Oxford University Press, pp.83-95.
- Thaler, Richard H. and Shlomo Benartzi. 2004. "Save More Tomorrow: Using Behavioral Economics to Increase Employee Saving," *Journal of Political Economy*, Vol. 112 (1) , pp. 164-187.

Table 1:		Demographics : Basic Summary Statistics			
Variable	Number of Participants	Percent of Sample	Mean	Median	Standard Deviation
Employment Status					
Part-time	37,464	59%			
Full-time	25,921	41%			
Total	63,385	100%			
Sex					
Female	52,161	82%			
Part-time Females	33,902	53%			
Full-time Females	18,259	29%			
Male	11,224	18%			
Part-time Males	3,562	6%			
Full-time Males	7,662	12%			
Total	63,385	100%			
2004 Salary					
Part-time	37,464	59%	\$ 15,370	\$ 14,444	\$ 7,151
Full-time	25,921	41%	\$ 35,162	\$ 26,907	\$ 25,983
Total	63,385	100%	\$ 23,464	\$ 18,387	\$ 20,025
Years Employed					
Part-time	37,464	59%	10.51	7.95	8.08
Full-time	25,921	41%	12.71	9.92	10.25
Total	63,385	100%	11.41	8.44	9.10
Age (Years)					
Part-time	37,464	59%	46.92	48.67	13.80
Full-time	25,921	41%	44.51	45.55	11.38
Total	63,385	100%	45.94	47.23	12.92
401(k) Balance as of 1/1/2004					
Part-time	37,464	59%	\$ 23,651.93	\$ 4,007.88	\$ 54,329.80
Full-time	25,921	41%	\$ 78,156.78	\$ 10,547.66	\$ 150,699.10
Total	63,385	100%	\$ 23,926.91	\$ 5,721.23	\$ 52,997.57

Table 2 Demographics: Tabulations of Salary, Employment Years, Age and Balance Ranges

	Number of Participants	Percent
2004 Salary Ranges		
Less than \$20,000	35,146	55%
\$20,000-\$30,000	16,917	27%
\$30,000-\$40,000	4,284	7%
\$40,000-\$60,000	2,870	5%
\$60,000-\$80,000	2,302	4%
Greater than \$80,000	1,866	3%
Total	63,385	100%
Years Employed Ranges		
Less than 2 years	6,604	10%
2-5 years	13,491	21%
5-10 years	14,934	24%
10-15 years	8,754	14%
15-20 years	7,330	12%
20-30 years	9,647	15%
Greater than 30 years	2,625	4%
Total	63,385	100%
Age Ranges		
Under 25	5,199	8%
25-30 years old	4,375	7%
30-40 years old	10,386	16%
40-50 years old	16,847	27%
50-60 years old	18,053	28%
60-65 years old	5,107	8%
Older than 65	3,418	5%
Total	63,385	100%
Total Balance Ranges		
No Balance	4,381	7%
\$1-\$1,000	11,853	19%
\$1,000- \$10,000	20,412	32%
\$10,000- \$25,000	11,012	17%
\$25,000- \$50,000	7,500	12%
\$50,000- \$75,000	3,271	5%
\$75,000-\$100,000	1,694	3%
Greater than \$100,000	3,262	5%
Total	63,385	100%

* Note percentages may not add to 100 percent because of rounding

Table 3: Demographic and Trading Detail By Pre-Evaluation Groupings

Panel A: Summary Statistics by Pre-Evaluation Grouping (as of September 15, 2004)

Pre-Evaluation Grouping	% of		Years			Age	% Full Time	Balance
	Count	Sample	Salary	Employed	Age			
Non-Users	53,646	85%	\$ 20,021.35	10.54	45.92	36%	\$ 17,064.68	
Online User	9,739	15%	\$ 42,425.64	16.21	46.04	68%	\$ 61,726.57	
Access System Once Over Time Period	3,683	6%	\$ 41,008.13	15.22	45.15	67%	\$ 53,783.02	
Access System More Than Once Over Time Period	2,127	3%	\$ 47,115.00	18.52	47.48	74%	\$ 83,611.97	
Enrolled Online No Session	3,929	6%	\$ 41,215.77	15.88	46.09	66%	\$ 57,324.91	
Total	63,385	100%	\$ 23,463.73	11.41	45.94	41%	\$ 23,926.91	

Panel B. Trading Based on Pre-Evaluation Groupings (Trading Period: March 1, 2004- September 15, 2004)

Pre-Evaluation Grouping (Number of Participants/ Percent of Pre-Evaluation Grouping)	Average Trades	Average					Three to Greater than		
		Zero Trades	One Trade	Two Trades	Five Trades	5 trades			
Non-Users	0.13	50,585	2,027	494	356	184			
Percent of Grouping Above		94%	4%	1%	1%	0%			
Online User	1.03	6,332	1,696	677	647	387			
Percent of Grouping Above		65%	17%	7%	7%	4%			
Access System Once Over Time Period	0.87	2,479	687	219	176	122			
Percent of Grouping Above		67%	19%	6%	5%	3%			
Access System More Than Once Over Time Period	1.92	878	542	265	272	170			
Percent of Grouping Above		41%	25%	12%	13%	8%			
Enrolled Online No Session	0.69	2,975	467	193	199	95			
Percent of Grouping Above		76%	12%	5%	5%	2%			
Total	0.27	56,917	3,723	1,171	1,003	571			
Percent of Total		90%	6%	2%	2%	1%			

* Note percentages may not add to 100 percent because of rounding

Table 4: Cross Tabulation of Pre-Evaluation and Post-Evaluation Groupings

This table relates participants' pre-evaluation groupings to their post-evaluation groupings. For example, as of September 15, 2004, 9,739 participants were considered Online Users. As of March 1, 2005, 78 percent of these participants remained online users, 18 percent became Managed Account Users, and 3.5 percent joined managed accounts and then dropped out. Of the group that dropped managed accounts, the individuals could become Online Users again or become Non-Users. There is no information regarding which choice they made.

Pre-Evaluation Grouping (as of September 15, 2004)	Post-Evaluation Groupings (as of March 1, 2005)				
	Dropped Managed Account	Managed Account User	Non-Users	Online User	Total
Non-Users	324 0.60%	4,947 9.22%	47,866 89.23%	509 0.95%	53,646 100%
Online User	343 3.52%	1,765 18.12%	0 0.00%	7,631 78.36%	9,739 100%
Total	667 1.05%	6,712 10.59%	47,866 75.52%	8,140 12.84%	63,385 100.00%

* Note percentages may not add to 100 percent because of rounding

Table 5: Demographic and Trading Detail By Post-Evaluation Grouping (as of March 1, 2005)

Panel A: Summary Statistics by Post-Evaluation Grouping (as of March 1, 2005)		% of		Years		% Full		
	No. of	Participants	Sample	Salary	Employed	Age	Time	Balance
Managed Account User		6,712	11%	\$ 27,766	13.77	49.48	46%	\$ 33,776
Dropped Managed Account		667	1%	\$ 44,585	18.83	51.06	64%	\$ 88,943
Non-Users		47,866	76%	\$ 19,583	10.28	45.48	36%	\$ 15,934
Online User		8,140	13%	\$ 41,007	15.47	45.25	66%	\$ 57,471
Total		63,385	100%	\$ 23,464	11.41	45.94	41%	\$ 23,927

Panel B. Trading Based on Post-Evaluation Groupings (Trading Period: September 16, 2004 - March 1, 2005)

Post Evaluation Grouping	No. of	Average	Zero	One Trade	Two	Three to	Greater
	Participants	Trades	Trades	Trade	Trades	Trades	than 5
Non-Users	47,866	0.11	45,508	1,578	355	268	157
<i>Percent of Post-Evaluation Non-Users</i>			95%	3%	1%	1%	0%
Online User	8,140	0.86	5,725	1,246	450	446	273
<i>Percent of Post-Evaluation Online Users</i>			70%	15%	6%	5%	3%
Total	56,006	0.20	51,233	2,824	805	714	430
<i>Percent of Total</i>			91%	5%	1%	1%	1%

* Note percentages may not add to 100 percent because of rounding

Table 6: Multinomial Logit Analysis

Marginal change and discrete change estimates from a multinomial logit regression are presented in this table. The four unordered choices studied are the participant's decision to 1) join managed accounts, 2) use the online advice system, 3) drop out of managed accounts or 4) to do nothing. For the continuous variables, the estimated marginal effects (variable change= Df/dx) and the discrete changes (variable change= Std Dev) for a one standard deviation change centered around the mean are presented. The marginal effect reported for the indicator variables is a discrete change from zero to 1 (variable change=0->1). These figures are calculated based on the means of the independent variables. **(*) indicate significance at the 1 percent (5 percent) level. Robust standard errors are calculated.

Panel A: Full Sample							N=	63,385
Variable	Variable Change	Managed Account User	Online User	Dropped Managed Account	Non-User	Mean		
Male	0->1	-0.0070 *	0.0096 **	-0.0019 **	-0.0007	0.18		
Full-time Salary	0->1	0.0005	0.0377 **	0.0020 **	-0.0402 **	0.41		
	Std Dev	0.0353	0.0554	0.0042	-0.0949	\$23.46	in thousands	
	Df/dx	0.0018 **	0.0028 **	0.0002 **	-0.0047 **			
Number of Years Employed	Std Dev	0.0071	0.0256	0.0020	-0.0347	11.41	years	
	Df/dx	0.0008 **	0.0028 **	0.0002 **	-0.0038 **			
Age Years	Std Dev	0.0291	-0.0219	0.0027	-0.0099	45.94	years	
	Df/dx	0.0022 **	-0.0017 **	0.0002 **	-0.0008 **			
401(k) Balance	Std Dev	0.0060	0.0095	0.0012	-0.0166	\$23,926.91		
	Df/dx	0.0000 **	0.0000 **	0.0000 **	-0.0000 **			

Panel B: Participants with Asset Allocations as of 1/1/2004							N=	59,007
Variable	Variable Change	Managed Account User	Online User	Dropped Managed Account	Non-User	Mean		
Male	0->1	-0.0019	0.0162 **	-0.0015 *	-0.0128 *	0.17		
Full-time Salary	0->1	0.0036	0.0422 **	0.0022 **	-0.0480 **	0.41		
	Std Dev	0.0310	0.0499	0.0039	-0.0847	\$24.04	in thousands	
	Df/dx	0.0015 **	0.0024 **	0.0002 **	-0.0042 **			
Number of Years Employed	Std Dev	0.0014	0.0190	0.0017	-0.0221	12.11	years	
	Df/dx	0.0002	0.0021 **	0.0002 **	-0.0024 **			
Age Years	Std Dev	0.0262	-0.0252	0.0027	-0.0036	46.72	years	
	Df/dx	0.0021 **	-0.0020 **	0.0002 **	-0.0003			
401(k) Balance	Std Dev	0.0045	0.0098	0.0011	-0.0155	\$25,702.20		
	Df/dx	0.0000 *	0.0000 **	0.0000 **	-0.0000 **			
Some Balance Invested in Lifestyle Funds	0->1	0.0676 **	0.0749 **	0.0061 **	-0.1485 **	0.34		

Chart 1: Post-Evaluation Grouping and Sex: Sample Proportions (in Decimal Fractions)

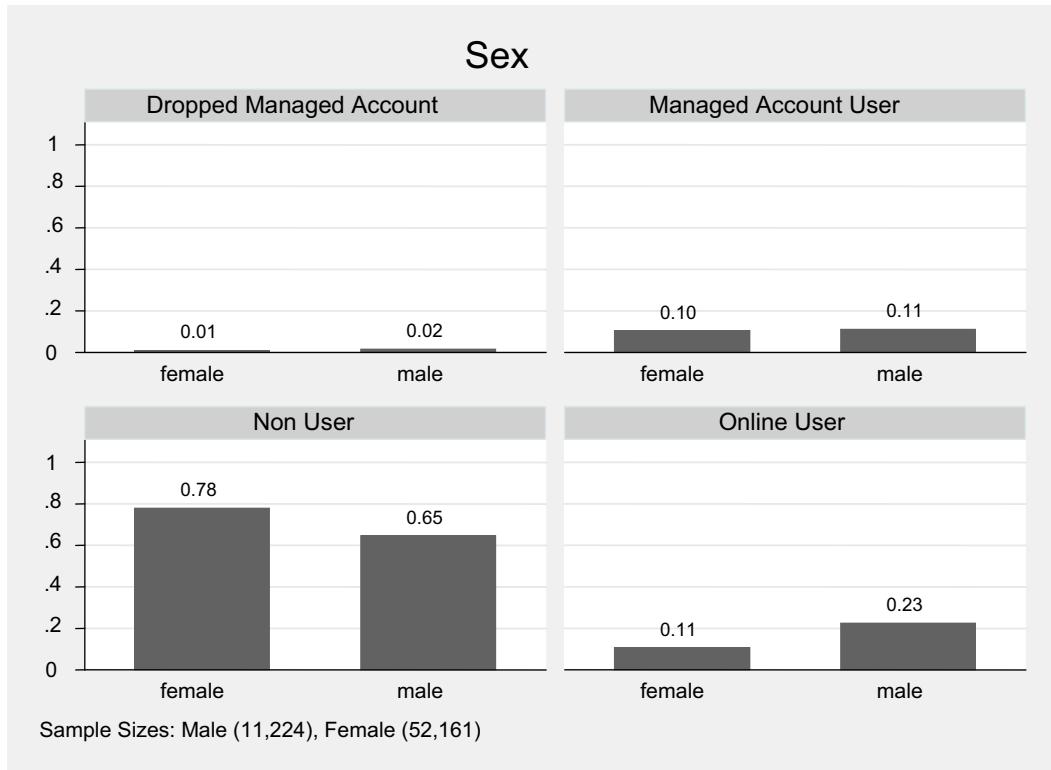


Chart 2: Post-Evaluation Groupings and Employment Status: Sample Proportions (in Decimal Fractions)

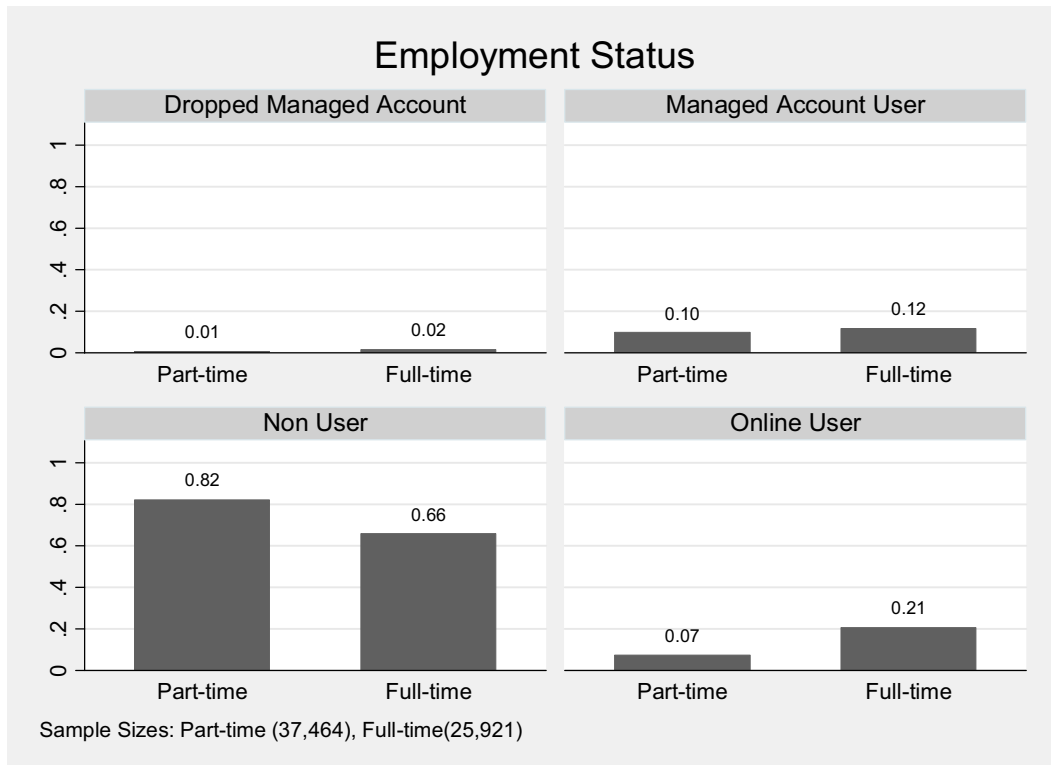


Chart 3: Post-Evaluation Groupings and Salary: Sample Proportions (in Decimal Fractions)

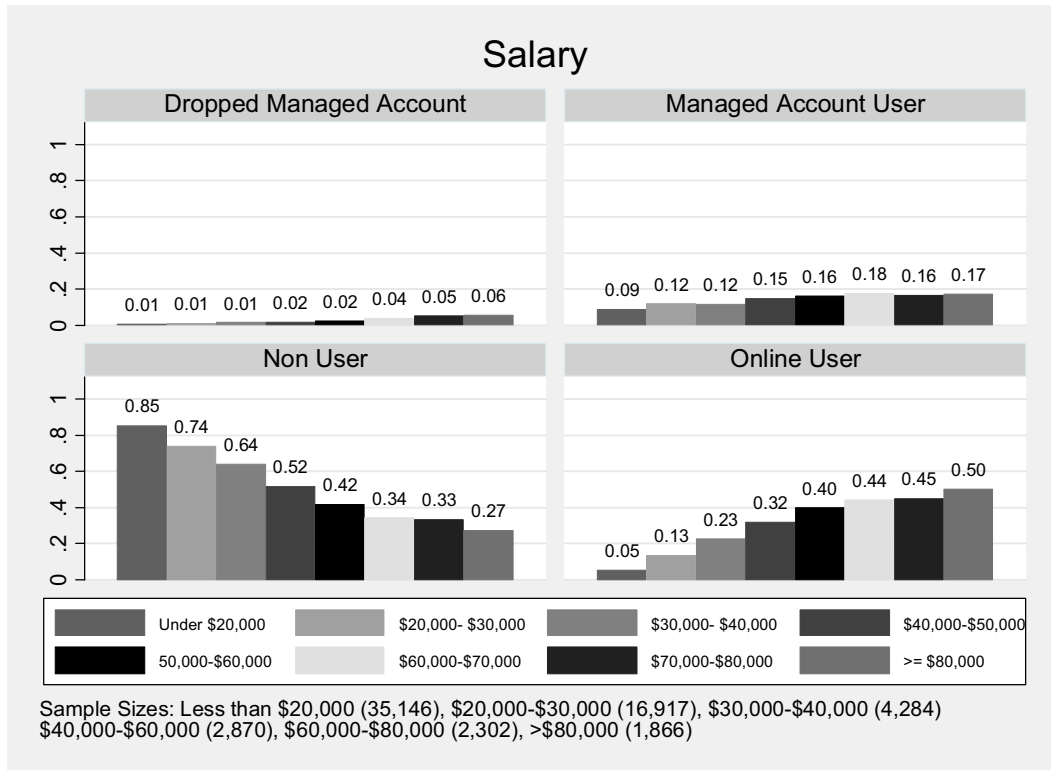


Chart 4: Post-Evaluation Groupings and Years Employed: Sample Proportions (in Decimal Fractions)

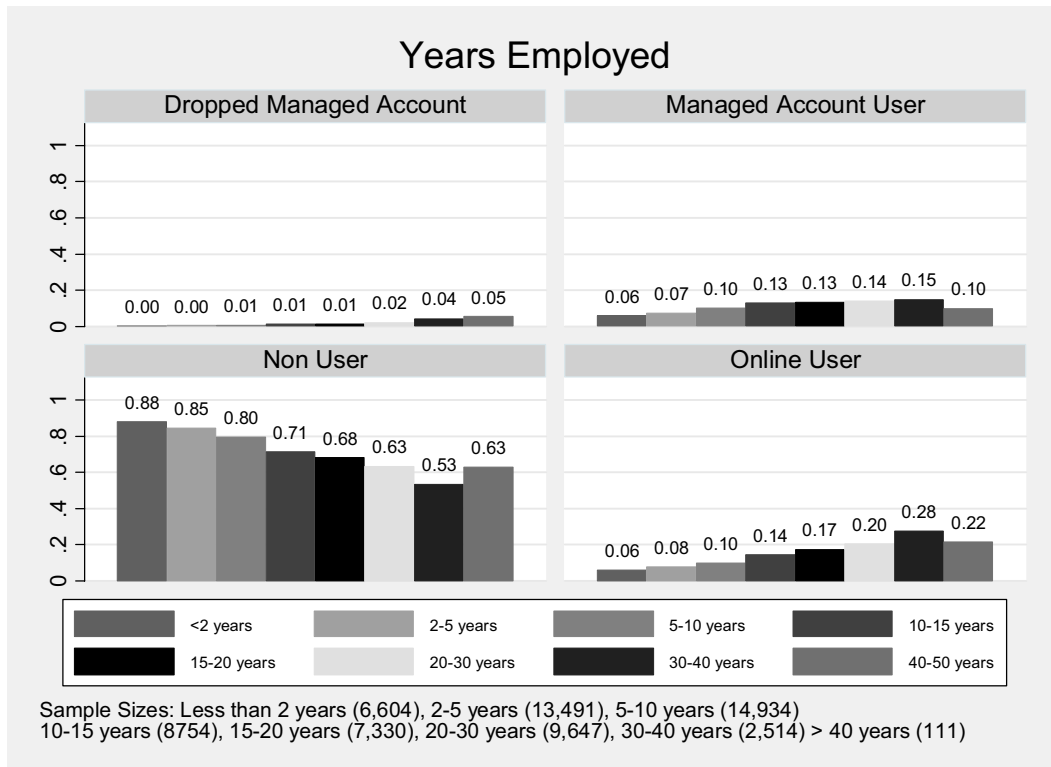


Chart 5: Post-Evaluation Groupings and Age: Sample Proportions (in Decimal Fractions)

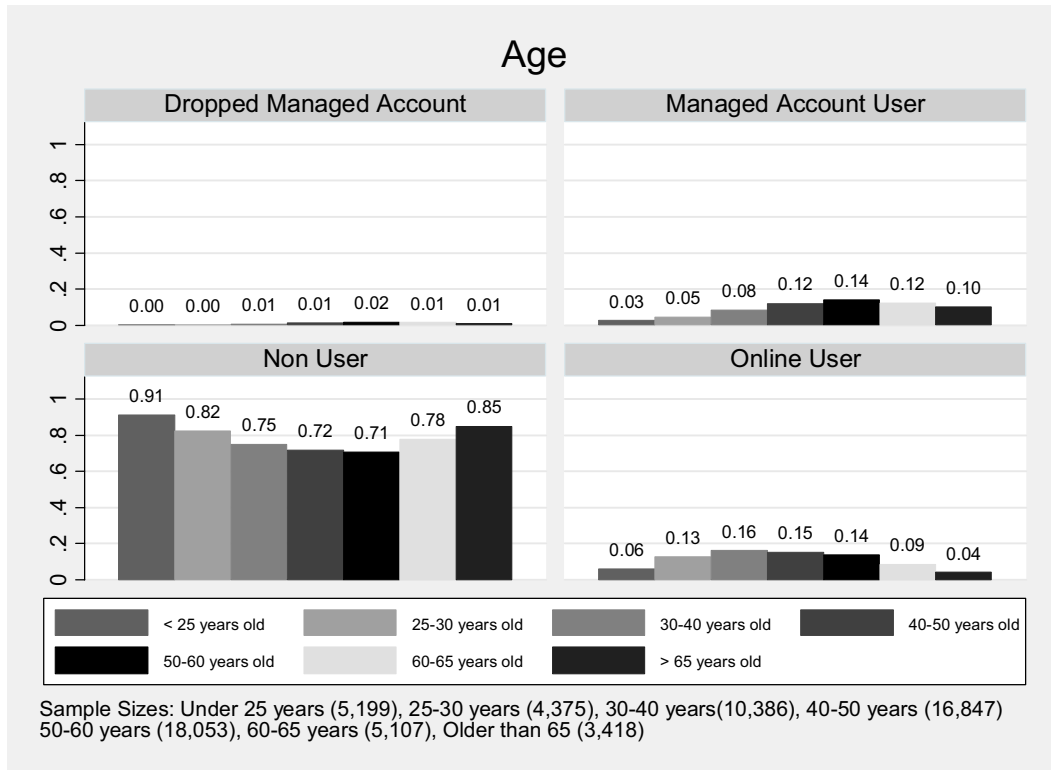
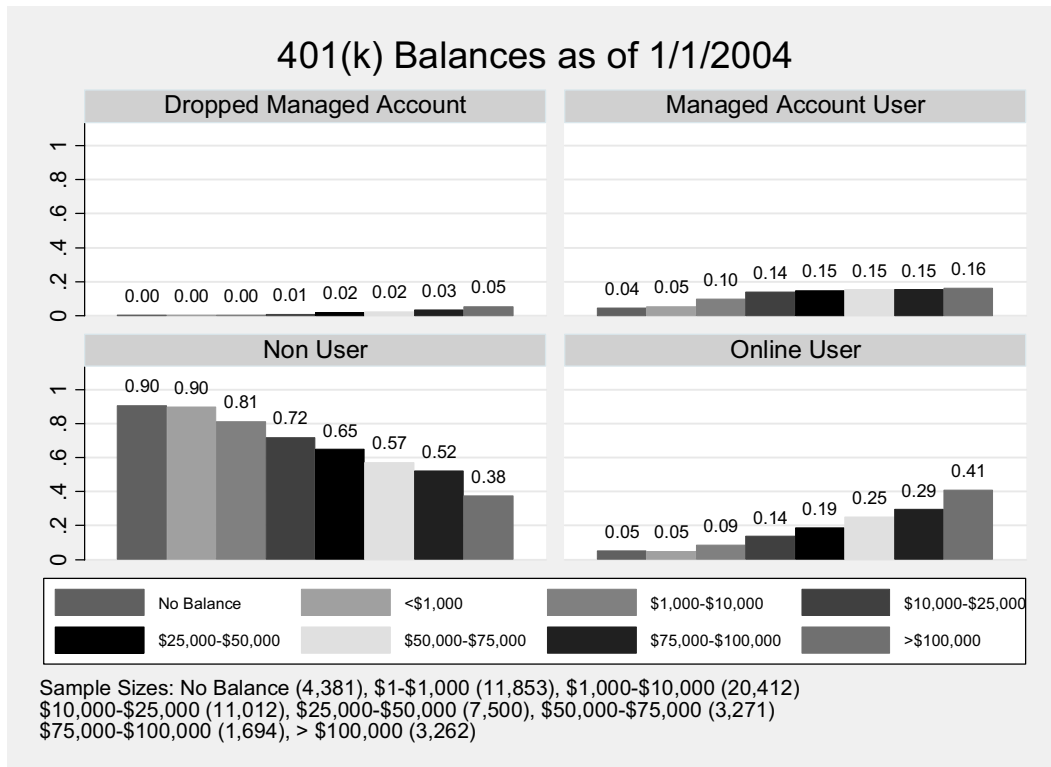


Chart 6: Post-Evaluation Groupings and 401(k) Balances: Sample Proportions (in Decimal Fractions)



RECENT WORKING PAPERS FROM THE
CENTER FOR RETIREMENT RESEARCH AT BOSTON COLLEGE

Working for a Good Retirement

Barbara A. Butrica, Karen E. Smith and C. Eugene Steuerle, March 2006

The Politics of Parallel Pensions: Lessons from the United Kingdom for the United States

R. Kent Weaver, February 2006

Cross-National Evidence on the Fiscal Burden of Public and Private Finance of Old-Age Consumption

Gary Burtless, February 2006

The Effects of Population Aging on Labor Demand

Bob Triest, Steven Sass and Margarita Sapozhnikov, February 2006

Financing Disability Benefits in a System of Individual Accounts: Lessons from International Experience

Patrick Wiese, February 2006

Long-Term Immigration Projection Methods: Current Practice and How to Improve it

Neil Howe and Richard Jackson, February 2006

Policies to Promote Labor Force Participation of Older Workers

Alicia H. Munnell, January 2006

Demographic Private Transfers in a Cross Section of Developing Countries

Donald Cox, Emanuela Galasso and Emmanuel Jimenez, January 2006

Making Maximum Use of Tax-Deferred Retirement Accounts

Janette Kawachi, Karen Smith and Eric Toder, January 2006

When the Nest Egg Cracks: Financial Consequences of Health Problems, Marital Status Changes, and Job Layoffs at Older Ages.

Richard W. Johnson, Gordon B.T. Mermin and Cori E. Uccello, December 2005

How Portfolios Evolve after Retirement: the Effect of Health Shocks.

Courtney Coile and Kevin Milligan, December 2005

All working papers are available on the Center for Retirement Research website (<http://www.bc.edu/crr>) and can be requested by e-mail (crr@bc.edu) or phone (617-552-1762).