Portfolio Choice and Trading in a Large 401(k) Plan

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We study nearly 7,000 retirement accounts during the April 1994–August 1998 period. Several interesting patterns emerge. Most asset allocations are extreme (either 100 percent or zero percent in equities) and there is inertia in asset allocations. Equity allocations are higher for males, married investors, and for investors with higher earnings and more seniority on the job; equity allocations are lower for older investors. There is very limited portfolio reshuffling, in sharp contrast to discount brokerage accounts. Daily changes in equity allocations correlate only weakly with same-day equity returns and do not correlate with future equity returns. (*JEL* G110)

Recent papers by Brad M. Barber and Terrance Odean (Odean, 1999; Barber and Odean, 2000, 2001) provide evidence on trading activity and portfolio performance of individual investors. Three behavioral implications emerge from their analysis: individual investors tend to trade too much (Odean, 1999), trading impairs realized portfolio returns (Odean, 1999; Barber and Odean, 2000), and men trade significantly more than women (Barber and Odean, 2001). These issues are important since assumptions about individuals' motives and trading behavior underlie all existing models of asset market equilibrium. Yet, these papers investigate a narrow subsample of individual investors: those who hold discount brokerage accounts. Because "overconfident" investors with an appetite for trading are likely to self-select into this sample, it may not be representative of the investor population at large.

Hence, it is useful to ask whether the stylized facts from previous research extend to broader classes of individual investors. Participants in 401(k) plans, for example, represent another potential database. Currently, about one-third of all workers (over 25 million) are enrolled in 401(k) plans, managing over $1 trillion in funds, and most plans allow for easy reshuffling of portfolios from one asset class to the other.

This paper follows a panel of nearly 7,000 401(k) accounts from a single plan for a period of over four years, from April 1994 through August 1998. The plan data include detailed information on participants' trading activity and asset allocations. The data also include demographic and employment information such as gender, age, marital status, salary, and tenure on the job.

Four main results emerge from the analysis of summary statistics for the plan. First, the distribution of allocations to stocks is strongly bimodal: 48 percent of the average annual equity allocations are zero, while 22 percent are 100 percent. Second, there is evidence of inertia in asset allocations: participants who entered the plan before April 1994, with a default allocation of 100 percent to the risk-free asset, have

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average equity allocations that are significantly lower than those of later entries, who had to make an explicit asset allocation choice.[1] Third, patterns of stock allocations by marital status, earnings, and job seniority are broadly consistent with the implications of normative models: Stock allocations are higher for married investors and for investors with higher earnings and more seniority on the job. Fourth, trading by participants is infrequent: Over 87 percent of the annual number of trades in the panel are zero and only 7 percent of the observations exceed one; the average number of annual transactions is 0.26, or one trade every 3.85 years, and average annual turnover is 16 percent. Infrequent rebalancing is consistent with the implications of models of optimal portfolio choice with realistic transaction costs (see, for example, Anthony W. Lynch and Balduzzi, 2000).[2]

This evidence contrasts with existing evidence drawn from discount brokerage accounts: Average annual transactions in our sample are less than one-fifth of the annual transactions in the discount brokerage account examined by Odean (1999), and annual portfolio turnover is less than one-fourth of the annual share turnover documented by Barber and Odean (2000). There are various possible explanations for this difference, in addition to the sample-selection bias mentioned above.[3] One explanation could be that the range of choices in our 401(k) plan is quite limited: there are only three equity funds and one fixed-income alternative. A 401(k) participant can change his asset allocation, but is completely unable to engage in stock-picking. If most of the trading in discount brokerage accounts is stock-picking, rather than asset allocation, then our results can be reconciled with those of Odean (1999) and Barber and Odean (2000). A second explanation could be that the 401(k) assets studied here are only a fraction of the financial assets held by an individual or a household. For example, based on the 1995 Survey of Consumer Finances (SCF), while most equity investment takes place through retirement plans (on average a share of 63 percent), the average fraction held directly (brokerage accounts) is a still substantial 20 percent (John Ameriks and Stephen P. Zeldes, 2000). Hence, it is possible that the same investor would trade frequently through his brokerage account, but would rebalance his 401(k) asset holdings infrequently.[4]

Regression tests examine how demographics and other characteristics jointly affect allocations and trading. Men invest more in equities than women and trade more actively than their female counterparts. Married investors invest more in equities than their single counterparts. A higher salary tends to make investors more aggressive in their allocations and increases trading activity. Entering the plan before 1994 leads to lower equity allocations and less trading. Age induces investors to allocate less to equities and to rebalance more frequently.

In addition to the effect of participants' characteristics on portfolio choices and trading, we examine whether investors react to contemporaneous and lagged market changes (feedback trading) or whether they are able to anticipate market movements (market timing). We perform these tests at the daily frequency by investigating the time-series properties of returns on participants' equity portfolios and of changes in participants' equity allocations. We find that overall changes in equity allocations correlate significantly and positively with the previous day's equity return, 0.31, while the correlation with the contemporaneous return is much weaker and only marginally significant, 0.12. As observed by John M. R. Chalmers et al. (1999), mutual fund investors have available a wildcard option in mutual fund shares, which they can exercise by responding to same-day returns. Hence, this evidence suggests that our investors take little, if any, advantage of the wildcard option. The correlations between allocation changes and returns over the following three days are small and insignificant, suggesting the absence of market-timing abilities.

[1] Other recent papers documenting inertia in 401(k) asset allocations are Brigitte C. Madrian and Dennis Shea (2000) and James J. Choi et al. (2001a, b).

[2] Nicholas Souleles (1999), on the other hand, *estimates* threshold models of securities purchases in the presence of transaction costs.

[3] We thank the referee for suggesting these possible explanations.

[4] Note, though, that while reallocating the 401(k) plan is free, commissions are incurred for trades in a brokerage account. This suggests that there should be *more* trading in the 401(k) account, all other things equal.

We then investigate correlations between returns and allocations for three subsamples of participants present throughout the sample: those who rebalance most frequently ("active" participants); those who realize the highest *ex post* portfolio returns ("successful" participants); and those who are both active traders and successful investors ("active and successful" participants). Interestingly, while correlation patterns for the most active traders mimic those found in the aggregate, the most successful participants in our sample do not react nor anticipate market returns. Hence, even the most successful investors in our sample do not take advantage of the wildcard option nor are they able to time the market.

Our study joins Ameriks and Zeldes (2000) in relating retirement-account portfolio behavior to various demographic variables and other participants' characteristics. Ameriks and Zeldes consider pooled cross-sectional data from the 1962–1963, 1983, 1989, 1992, 1995, and 1998 SCF, and a panel data of TIAA-CREF accounts for the 1987–1999 period. Our study differs from theirs in two main respects. First, Ameriks and Zeldes focus on the effect of one demographic variable, age, on equity allocations. Our study considers the effects of several additional demographic variables and other characteristics, such as gender, marital status, time in the plan, salary, and time on the job. Second, Ameriks and Zeldes focus on equity allocations, while our study considers the effects of participants' characteristics on trading activity, in addition to equity allocations.

Other existing studies of 401(k) and other retirement plans [e.g., Vickie L. Bajtelsmit and Jack L. VanDerhei (1997); Zvi Bodie and Dwight B. Crane (1997); Richard P. Hinz et al. (1997); and Sundén and Brian J. Surette (1998)] focus on asset allocation choices *at one point in time.* What distinguishes our study and Ameriks and Zeldes (2000) from the previous literature is that we follow the plan participants *over time.* The time-series dimension allows us to investigate how equity allocations change as individuals age and gain seniority on the job. The time-series dimension also allows us to model individual equity allocations as a function of common time effects. Finally, we are able to investigate trading activity, which can only be measured over a period of time.[5]

This paper is organized as follows. Section I describes the data set. Section II presents summary statistics concerning asset allocation decisions and trading behavior. Section III describes the regression results. Section IV investigates the timing of changes in equity allocations. Section V concludes.

I. Data

The data in this study come from the 401(k) plan for a large firm. The data set includes information on 6,778 participants for the time period April 1994–August 1998.[6] The plan data set originally included information for a larger sample of participants.[7] From this data set, we eliminated participants who were no longer in the plan as of April 1994. Further, participants were eliminated due to data errors.[8] Finally, we eliminated participants who were in the plan for less than one full year, and we consider year/participant observations as valid only if the participant was in the plan for the whole year.[9] The reason for this choice is that observations for a fraction of a year can introduce substantial noise in the analysis. For example, consider a participant who is in the plan only for one month during a given year and rebalances his allocations once during that month, his annualized number of trades would be 12. This is most likely to exceed the annual number of trades for

[5] Less closely related to the present study is Shlomo Benartzi and Richard Thaler (2001). Their study considers a cross-section of plans, rather than a cross-section of individuals, and studies how allocations at the *plan level* change as a function of the investment choices allowed in the plan.

[6] Citistreet (formerly State Street Global Advisors) generously supplied the data used for this study.

[7] Note that this data set does not include a complete list of those individuals who were eligible but not participating. Therefore, it is impossible to quantify or comment on the participation rate in this plan.

[8] Some individuals did not have unique participant numbers, making it difficult to match demographic and employment information with trading activity. Some participants were deleted because at some point in time their asset allocation percentages did not sum to 100 percent; and other participants were eliminated because of missing plan entry dates.

[9] Participants who were in the plan only in 1994 and 1998 were eliminated if they were not in the plan from April to December and from January to August, respectively.

TABLE 1—DESCRIPTIVE PLAN STATISTICS

	Observations	Percent	Mean	Standard deviation	Minimum	Maximum
Gender:						
Male	5,298	78.16				
Female	1,478	21.81				
Unknown	2	0.03				
Total	6,778	100.00				
Marital status:						
Married	5,123	75.58				
Unmarried	1,439	21.23				
Unknown	216	3.19				
Total	6,778	100.00				
Married and male	4,292	63.33				
Salary:	6,024		\$69,389	\$35,353	\$13,384	\$1,404,031
Entry-exit:						
In plan entire time	4,783	70.57				
Enter plan late	951	14.03				
Leave plan early	999	14.74				
Enter late and leave early	45	0.66				
Total	6,778	100.00				
Age:	6,699		39.94	8.32	19.88	76.84
Years employed:	6,778		9.31	4.59	0.00	17.94

Notes: The table describes general statistics concerning the plan participants: gender, marital status (as of August 1998), 1997 annual salary (as of October 1997), entry and exit in and out of the plan, age (as of August 1998), and time employed (as of August 1998).

that participant had he been in the plan for the whole year. The plan data include detailed information on participants' trading activity and asset allocations.[10]

A. *Participants' Characteristics*

Descriptive statistics on the demographic characteristics of the participants are presented in Table 1. Marital status, time employed, and age are measured as of August 1998, while salary is the 1997 annual salary measured as of October 1997.

The majority of the individuals in the sample are males (78 percent) and married (76 percent). The average salary is \$69,389. Almost three-quarters of the participants stay in the plan for the entire time period. The remaining one-quarter either enter the plan after April 1, 1994 and remain until the end of the time period; are in the plan as of April 1, 1994 and leave before August 1998; or enter the plan after April 1, 1994 and leave before August 1998.[11] The average age of plan participants is 40 years old. On average participants have been employed by the company for approximately nine years.

To explore how representative our sample is relative to the U.S. population, Table 2 compares earnings by age group in our sample to earnings by age group from the Current Population Survey (CPS) 1997 data. Our sample differs from the U.S. population in two main

[10] Although the plan existed before April of 1994, data before this date is not relevant to this study. Before April 1994 participants were only able to invest in Guaranteed Investment Contracts (GICs), thus eliminating the possibility of studying any trading activity or asset allocation choices during this time period. In addition to the 401(k) plan, the plan's sponsor offers participants a defined benefit plan. There is no specific information available related to this defined benefit plan because it is not administered through CitiStreet.

[11] Note that this study considers a participant out of the plan when the participant receives his/her first distribution unless an allocation change occurs after the distribution. In that case, the last allocation change after the first distribution is considered the last date in the plan. A distribution can occur before or after the participant's termination date if it exists.

TABLE 2—COMPARISON OF AGE–SALARY STRUCTURE FOR U.S. POPULATION AND 401(K) SAMPLE

Age range	Median 1997 salary: U.S. population	Median 1997 salary: 401(k) plan
Under 35 years old	$22,846	$62,835
35–44 years old	$30,880	$64,470
45–54 years old	$33,106	$68,649
55–64 years old	$29,434	$73,450
65+ years old	$21,032	$69,813

Notes: The table presents a comparison between the median salary by age group for the U.S. population at large and the 401(k) plan participants. The source for the U.S. population data is CPS 1997.

respects. First, for all age groups, participants in our plan earn substantially higher salaries than the population in general: two to three times higher. Second, although median salaries peak with the 45–54 age group for the U.S. population, they peak with the 55–64 age group for our sample. Finally, while for the U.S. population the 65+ age group earns the lowest median annual salary, in our sample the oldest age group earns the second-highest salary. Hence, we are considering a sample of investors who earn substantially more than the rest of the U.S. population, and the association between age and income is more strongly positive.

B. *Investment Choices*

The plan offers participants four investment choices: a Guarantee Income Contract (GIC) fund; a large-stock domestic equity fund; a small/medium-stock equity fund; and an international equity fund. Alternatively, participants can invest in one of four pre-mixed "balanced" portfolios comprised of the previously mentioned funds.

For the purpose of this study, participants' asset choices are divided into two main categories: equity investments and bond investments. Investment in the GIC fund is considered a bond investment while investment in the large-stock domestic equity fund, small/medium-stock domestic equity fund, or international equity fund are considered equity investments. If a participant chooses to invest in a pre-mixed balanced fund, the investment is divided according to the asset breakdown for that fund.

The plan allows participants to freely change their asset allocations on a daily basis. When the asset allocation is changed, the participants' funds are redistributed to match the new allocation and all future contributions by the participant are invested according to the new allocation. The plan data include a record of the date of the allocation change and the new and old allocations.

In our analysis we consider both *desired* and *actual* allocations. Desired allocations are the fractions of *new contributions* invested in the different asset classes. Actual allocations are the fractions of the *existing assets in the account* invested in the different asset classes. Desired and actual allocations coincide immediately after a rebalancing, but then tend to drift apart because of the different returns on the different funds.

II. Allocations and Trading: Summary Statistics

This section summarizes asset allocation choices and trading behavior. This evidence is a "nonparametric" description of the data set, which usefully complements the regression analysis of the following section.

We present summary statistics for the panel data set to be used in the regression analysis. For asset allocations and trading measures, we follow the 6,778 participants for five years, for a total of 28,775 observations.

Each table is organized in two panels. Panel A presents the frequency distribution of all the observations in the panel data set. The observations are then sorted by year, gender, marital status (as of August 1998), 1997 annual salary (as of October 1997), time of entry in the plan (before or after April 1994), age (as of year of the observation), and time employed (as of year of the observation). Means and standard deviations for these subsamples are presented in Panel B of each table.[12]

A. *Equity Allocations*

Table 3 shows annual averages of monthly desired equity allocations. We focus on desired

[12] We also calculated medians by subgroups. These are not reported in the tables. In the case of equity allocations, medians by subgroup tend to follow the same patterns as the means. In the case of measures of trading activity, medians are almost always zero, and hence are not informative.

TABLE 3—EQUITY ALLOCATIONS

Panel A: Distribution

Range	Percent
$x = 0$	47.61
$0 < x < 20$	1.95
$20 \leq x < 40$	4.00
$40 \leq x < 60$	6.59
$60 \leq x < 80$	11.10
$80 \leq x < 100$	7.01
$x = 100$	21.73

Panel B: Statistics by Group

	Observations	Mean	Standard deviation
All	28,755	40.54	43.08
Sort by year:			
1994	5,782	28.07	39.52
1995	5,704	30.23**	39.86
1996	5,857	40.68**	42.68
1997	5,679	48.27**	43.16
1998	5,733	55.55**	43.60
Gender:			
Male	22,737	42.45	43.27
Female	6,008	33.37**	41.59
Unknown	10	0.00	0.00
Marital status:			
Married	22,237	42.88	43.15
Unmarried	5,779	36.52**	42.72
Unknown	739	1.34	9.68
Annual salary:			
Under $25,000	141	30.23	38.82
$25,000-$49,999	1,291	43.30*	43.81
$50,000-$74,999	18,898	37.86	42.60
$75,000-$99,999	4,861	56.25**	42.46
$100,000+	1,532	57.76**	39.67
Unknown	2,032	13.83	30.94
Time of entry:			
Pre-1994	26,438	39.97	43.00
Post-1994	2,317	47.04**	43.42
Age:			
Under 35 years old	10,238	37.50**	43.06
35–44 years old	12,033	42.50	43.41
45–54 years old	5,345	44.01	42.57
55–64 years old	919	37.85*	39.79
65+ years old	54	4.75**	18.64
Unknown	166	0.00	0.00
Time employed:			
0–5 years	8,456	30.86**	41.23
6–10 years	8,956	41.49**	43.53
11–15 years	9,783	44.55	42.75
16–20 years	1,560	62.34**	39.57

Notes: The table presents statistics for average annual equity allocations (in percents). In Panel A, we consider the frequency distribution of the observations in the panel. In Panel B, we sort observations by year, gender, marital status (as of August 1998), 1997 annual salary (as of October 1997), time of entry in the plan (before or after April 1994), age (as of year of the observation), and time employed (as of year of the observation). For each sorting, we test the null hypotheses that the mean of each subcategory equals the mean of the reference subcategory (bold). One (two) asterisk(s) denote rejection in a two-tailed test at the 5-percent (1-percent) significance level. Test statistics are adjusted for serial correlation and heteroskedasticity.

equity allocations, rather than actual allocations, because they are more likely to reflect a participant's intentions. Most average annual allocations are at the two extremes of the admissible range[13]: 47.61 percent of the equity allocations in the panel are zero, while 21.73 percent of the allocations are 100 percent. Hence the distribution is strongly bimodal. The overall average allocation to equities is 40.54 percent, with a standard deviation of 43.08 percent.

Asset allocations vary over time with a marked positive trend: the average annual equity allocation monotonically increases from 28.07 percent in 1994 to 55.55 percent in 1998. It appears that participants responded to the bull market of 1994–1998 by adjusting their allocations upwards.[14]

Asset allocations also vary systematically with participants' characteristics. First, the average equity allocation is significantly higher for men than for women: 42.45 percent as opposed to 33.37 percent.[15] Second, marital status matters.[16] The average allocation for married participants is 42.88 percent, while the average for single participants is 36.52 percent. One possible explanation for this pattern has to do with idiosyncratic labor-income shocks. Couples with dual earners enjoy some diversification of these shocks. This makes a married individual's nonfinancial income less risky and should induce more aggressive asset allocations relative to single investors. A second possible explanation has to do with the stronger bequest motive for married couples.[17] The bequest motive lengthens an investor's horizon beyond his life span and, as argued below, models of opti-

[13] Investors cannot take short positions within the plan.

[14] The cumulative return on the S&P 500 index for that period was 137 percent.

[15] We test the equality of means by regressing observations on a constant and one or more dummies. The coefficient(s) on the dummies capture the difference in means. By (marginally) significant, we denote a coefficient significantly different from zero at the (5-percent) 1-percent level in a two-sided test. Statistics in these and all other regression tests in the paper are adjusted for serial correlation and heteroskedasticity; see Appendix for details.

[16] Sundén and Surette (1998) suggest that the interaction between gender and marital status may also play a role. This hypothesis is investigated later on in the regression analysis, where we use as an explanatory variable an interaction dummy for plan participants who are male *and* married.

[17] We thank Ed Kane for suggesting this point.

mal portfolio choice predict a higher allocation to equities the longer the time horizon.

Third, a marked variation of allocations exists by salary group. We expect a positive correlation between salary and equity allocation because higher annual earnings translate into a higher stock of human capital. For most individuals, labor income is either risk free or is dominated by person-specific risk that is only weakly correlated with stock returns.[18] Hence, human capital is a relatively safe investment and investors should compensate for the higher stock of human capital with a higher investment in risky assets, i.e., stocks.[19] A higher annual salary may also be interpreted as a proxy for education and financial sophistication, both of which should correlate positively with the allocation to equities. All these elements predict a positive correlation between salary and equity allocation. This positive correlation arises for all salary ranges, with the exception of the \$50,000–\$74,999 range. Overall, we have an increase of equity allocations from 30.23 percent (Under \$25,000) to 57.76 percent (\$100,000+).

Fourth, participants who entered the plan before 1994 tend to allocate significantly less to equities than later entries: 39.97 percent as opposed to 47.04 percent. Since participants who entered the plan before were assigned a 100-percent allocation to the GIC fund by default, this is consistent with some inertia in their revision of asset allocations.[20]

We next investigate how asset allocations vary according to age. Mean allocations initially increase as a function of age and then tend to decrease. Average allocations equal 37.50 percent, 42.50 percent, and 44.01 percent for the participants under 35, 35 to 44, and 45 to 54. For the 55 to 64 group the average allocation declines to 37.85 percent; while the 65 and older group allocates an average of 4.75 percent to stocks. This pattern is roughly consistent with the findings of Ameriks and Zeldes (2000). Based on an examination of TIAA-CREF data covering the 1987–1996 period, they show that equity shares in financial assets have a hump-shape pattern with age.[21]

The declining portion of the hump-shape pattern is consistent with models of optimal portfolio choice. As shown by Balduzzi and Lynch (1999) and Lynch and Balduzzi (2000), the time-series properties of U.S. stock returns are such that an investor with long-term objectives tends to allocate a larger fraction of his wealth to stocks than a short-term investor. The positive hedging demand for equity decreases as the investor ages. In addition, asset allocations should change over the life cycle as a function of the stock of nontradable human wealth. As shown by Jagannathan and Kocherlachota (1996), when investors are young, they have a long stream of future income. As they age, this stream shortens, so the value of their human capital falls. The best way for investors to respond to this situation is to shift the risk composition of their financial wealth in order to offset the decline in the value of their human capital. So, most investors need to shift their financial wealth toward bonds and away from stocks as they age to make up for the loss in human capital. In addition, the model of Bodie et al. (1992) incorporates the feature that individuals have some ability to change their supply of labor in response to realized returns on their assets: a low return on financial wealth can be partially "hedged" by increasing labor supply. It is reasonable to hypothesize that, for most individuals, the degree of labor flexibility diminishes over the life cycle. For this reason, the effective human capital on which the individual can draw also declines, leading to more conservative investment behavior as retirement nears.

Finally, we investigate the association between tenure on the job and equity allocations. Average equity allocations for employees who were with the company five years or less average 30.86 percent. Average equity allocations then steadily increase, to reach 62.34 percent for participants who were with the company 16 to 20 years. This pattern is consistent with the

[18] The weak correlation between stock returns and labor income is documented, for example, by Miles S. Kimball (1993) and Douglas W. Elmendorf and Kimball (2000).

[19] Portfolio allocation in the presence of labor income, and hence of human capital, is studied in the context of dynamic optimization models such as those of Bodie et al. (1992) and Ravi Jagannathan and Narayana R. Kocherlakota (1996).

[20] This is consistent with the findings of Hinz et al. (1997).

[21] This is based on a specification that includes age and time effects, excluding cohort effects.

notion that as seniority increases, so does job security. This makes human capital less risky, which makes it optimal to increase financial exposure to the riskier assets.

When interpreting the allocation decisions, it is important to bear in mind that the 401(k) plan is just one of the assets in a household's overall portfolio. The question is how the allocation of retirement assets compares to the allocation of the nonretirement portfolio. Cori E. Uccello (2000) uses information from the 1998 SCF and concludes that families tend to invest their retirement saving in a very similar fashion to their nonpension assets. That is, if a participant holds mostly equities in their 401(k) plan, he or she is also likely to hold a similar share of equities in the nonretirement part of the portfolio.

B. *Trading Activity*

Table 4 measures trading activity by the number of times a participant changes portfolio allocations every year. These trades include any reallocations among the eight funds available for investment: the four basic funds and four balanced portfolios.[22]

Since employees who joined the plan before April 1994 started with a 100-percent allocation to the GIC fund, these participants had to adjust their allocations to invest in equities. Hence, this first trade is very different in nature from all other trades and it is excluded from all measures of trading activity.[23]

About 88 percent of the annual number of trades are zero: that is no trades. Roughly 6 percent of the observations are of one trade per year and only 0.19 percent of the observations exceed 10 trades per year. Overall, the average number of trades per year is 0.26, or one trade every 3.85 years. These statistics indicate very limited trading activity on the part of the participants in the sample.[24]

TABLE 4—NUMBER OF TRADES

Panel A: Distribution

Range	Percent
$x = 0$	87.55
$0 < x \leq 1$	5.60
$1 < x \leq 5$	6.20
$5 < x \leq 10$	0.47
$10 < x \leq 39$	0.19

Panel B: Statistics by Group

	Observations	Mean	Standard deviation
All	28,755	0.26	1.09
Sort by year:			
1994	5,782	0.16	0.93
1995	5,704	0.23**	1.22
1996	5,857	0.26**	0.99
1997	5,679	0.34**	1.13
1998	5,733	0.30**	1.15
Gender:			
Male	22,737	0.28	1.17
Female	6,008	0.18**	0.74
Unknown	10	0.00	0.00
Marital status:			
Married	22,237	0.28	1.17
Unmarried	5,779	0.21**	0.81
Unknown	739	0.01	0.15
Salary:			
Under $25,000	141	0.11**	0.40
$25,000–$49,999	1,291	0.16*	0.62
$50,000–$74,999	18,898	0.22	0.97
$75,000–$99,999	4,861	0.39**	1.40
$100,000+	1,532	0.66**	1.95
Unknown	2,032	0.08	0.41
Time of entry:			
Pre-1994	26,438	0.26	1.12
Post-1994	2,317	0.22*	0.74
Age:			
Under 35 years old	10,238	0.17**	0.78
35–44 years old	12,033	0.27	1.16
45–54 years old	5,345	0.36**	1.27
55–64 years old	919	0.60**	1.82
65+ years old	54	0.03**	0.20
Unknown	166	0.00	0.00
Time employed:			
0–5 years	8,456	0.14**	0.70
6–10 years	8,956	0.20**	0.79
11–15 years	9,783	0.35	1.37
16–20 years	1,560	0.64**	1.94

Notes: The table presents statistics on annual number of trades. In Panel A, we consider the frequency distribution of the observations in the panel. In Panel B, we sort observations by year, gender, marital status (as of August 1998), 1997 annual salary (as of October 1997), time of entry in the plan (before or after April 1994), age (as of year of the observation), and time employed (as of year of the observation). For each sorting, we test the null hypotheses that the mean of each subcategory equals the mean of the reference subcategory (bold). One (two) asterisk(s) denote rejection in a two-tailed test at the 5-percent (1-percent) significance level. Test statistics are adjusted for serial correlation and heteroskedasticity.

[22] Number of trades and turnover for 1994 and 1998, which are not full years, are annualized.

[23] It is worth noting that 35 percent of the employees who joined the plan before April 1994 keep their allocation entirely in the GIC and never trade during the sample.

[24] Ameriks and Zeldes (2000) confirm our evidence of limited trading in 401(k) plans. They find that almost half of the investors in a sample of TIAA-CREF accounts made no changes to their allocations during the 1987–1996 period.

Theory tells us that, in the absence of transaction costs, it is optimal for an investor to rebalance his portfolio continuously. On the other hand, fixed transaction costs lead to infrequent rebalancing by discrete amounts. Since no explicit fee is charged when investors in our sample change allocations,[25] the type of transaction costs they face must be *implicit:* the opportunity cost of spending time considering one's portfolio choices, for example.[26]

Hence, it is interesting to ask what number of trades per year is optimal for an investor facing realistic fixed transaction costs. Lynch and Balduzzi (2000) perform this type of exercise. They consider an investor choosing between U.S. stocks and a risk-free asset. The investor has to pay a fixed fee of either 0.01 percent or 0.1 percent of the portfolio value ($10 and $100 for a $100,000 portfolio, respectively) for every trade. Lynch and Balduzzi predict that an investor with a ten-year investment horizon who uses the *unconditional* distribution of U.S. stock returns averages 0.37 and 0.16 trades per year, depending on the fee. Hence, the average number of annual trades realized by our investors, 0.26, falls squarely within the range calculated in their paper. Interestingly, they also predict that an investor using the *conditional* distribution of stock returns, hence being aware of predictability, rebalances much more frequently: on average 1.8 and 0.63 times per year. Hence, our sample also provides an indirect indication that investors do not try to time the market, and make rebalancing decisions with the long-run properties of asset returns in mind.

Our evidence on trading frequency seems to contrast with the evidence on discount brokerage accounts reported by Odean (1999). Odean examines trading activity in 10,000 accounts from January 1987 through December 1993, finding that investors trade on average 1.44 times per year, which is 5.5 times higher than in our sample. As argued earlier, this difference might be due to several factors, including sample-selection, and the limited range of investment choices offered in our 401(k) plan.

Trading activity in our sample varies over time with an overall positive trend. While in 1994 there were only an average of 0.16 trades per year, this average grows to 0.34 by 1997, to stabilize at 0.30 in 1998.

We then investigate patterns of trading activity according to participants' characteristics. Males trade a significant 56 percent more than females, where the average number of annual trades is 0.28 for males and 0.18 for females. Marital status also is significant. Married investors trade significantly more than single investors: an average of 0.28 times a year, as opposed to 0.21 times for their single colleagues.

Trading activity increases with salary. Participants earning less than $25,000 average 0.11 annual trades, while participants with salaries in excess of $100,000 average 0.66 trades per year. Presumably, participants earning a higher salary manage a larger portfolio, for which the benefits of rebalancing are more substantial. As argued earlier, salary may also proxy for financial sophistication, which is likely to be positively correlated with trading activity.

Trading activity also increases with age. While participants below age 35 trade on average of 0.17 time per year, participants in the 55–64 age group trade an average of 0.60 times. The exception to this pattern is trading among participants 65 and older, who average only 0.03 trades per year. This higher trading activity among participants closer to retirement is consistent with the notion that as investors age, the investors' financial wealth increases relative to their human capital. This makes the need of an efficient allocation more pressing, hence inducing higher trading activity. The lower trading activity among the oldest plan participants can also be rationalized: these investors are mainly invested (95 percent on average) in the GIC fund, which is the safest investment option. This makes further trading towards the safe asset unlikely.

Average annual trades tend to increase with job seniority. Employees who are with the company up to five years average 0.14 trades per year. In contrast, employees who are with the company for 16 to 20 years average 0.64 trades per year. This pattern is consistent with the

[25] Plan fees are charged against the aggregate account balance of participants.

[26] Choi et al. (2000) also provide indirect evidence of the existence of implicit transaction costs. They show that the introduction of web-based trading (and hence the reduction of implicit transaction costs) in two corporate 401(k) plans substantially increases trading frequency and portfolio turnover.

notion that higher job security, associated with tenure on the job, leads to more aggressive investing both in terms of the investment choices and rebalancing activity.

Table 5 reports statistics on trading activity as measured by annual portfolio turnover. Portfolio turnover is the total percentage change in a participant's actual allocations during each year in the plan.[27] As with the number of trades, we find evidence of moderate trading activity: most observations, 87.55 percent, have zero annual turnover and only 4.30 percent of the observations have more than 100-percent annual turnover. Average annual turnover for the sample is 16.20 percent. This figure is less than one-fourth of the average annual turnovers reported by Barber and Odean (2000) for their discount brokerage accounts sample, in which *monthly* turnovers averaged 6 to 7 percent.[28]

Since turnover correlates strongly with the number of trades, patterns in turnover over time and according to participants' characteristics closely mirror those documented for the number of trades. Turnover increases steadily during the four years of the sample, from 9.18 percent in 1994 to 21.69 percent in 1997, and then flattens to 20.28 percent in 1998. Men rebalance significantly more than women (17.47 percent v. 11.43 percent) and married participants rebalance slightly more than single participants (17.30 percent v. 13.97 percent). Interestingly, our evidence on portfolio turnover by gender is similar to the results of Barber and Odean (2001). They find that average share turnover is 43 percent higher for men than it is for women in their sample from a large brokerage firm. In our sample, portfolio turnover is 53 percent higher for men than it is for women. We find

TABLE 5—TURNOVER

Panel A: Distribution

Range	Percent
$x = 0$	87.55
$0 < x \leq 10$	0.35
$10 < x \leq 100$	7.80
$100 < x \leq 2{,}744$	4.30

Panel B: Statistics by Group

	Observations	Mean	Standard deviation
All	28,755	16.20	77.21
Sort by year:			
1994	5,782	9.18	53.08
1995	5,704	13.42**	72.58
1996	5,857	16.54**	70.20
1997	5,679	21.69**	85.24
1998	5,733	20.28**	97.39
Gender:			
Male	22,737	17.47	81.34
Female	6,008	11.43**	58.83
Unknown	10	0.00	0.00
Marital status:			
Married	22,237	17.30	81.58
Unmarried	5,779	13.97*	63.22
Unknown	739	0.82	10.84
Salary:			
Under $25,000	141	7.87	34.74
$25,000–$49,999	1,291	10.80	47.48
$50,000–$74,999	18,898	14.18	67.50
$75,000–$99,999	4,861	23.11**	94.87
$100,000+	1,532	39.43**	151.91
Unknown	2,032	5.06	29.22
Time of entry:			
Pre-1994	26,438	16.38	79.05
Post-1994	2,317	14.18	51.62
Age:			
Under 35 years old	10,238	10.40**	50.96
35–44 years old	12,033	17.14	82.34
45–54 years old	5,345	22.28*	90.92
55–64 years old	919	36.93**	140.17
65+ years old	54	2.78**	20.45
Unknown	166	0.00	0.00
Time employed:			
0–5 years	8,456	9.17**	47.73
6–10 years	8,956	12.37**	52.08
11–15 years	9,783	21.61	92.51
16–20 years	1,560	42.46**	164.58

Notes: The table presents statistics on annual portfolio turnover (in percents). In Panel A, we consider the frequency distribution of the observations in the panel. In Panel B, we sort observations by year, gender, marital status (as of August 1998), 1997 annual salary (as of October 1997), time of entry in the plan (before or after April 1994), age (as of year of the observation), and time employed (as of year of the observation). For each sorting, we test the null hypotheses that the mean of each subcategory equals the mean of the reference subcategory (bold). One (two) asterisk(s) denote rejection in a two-tailed test at the 5-percent (1-percent) significance level. Test statistics are adjusted for serial correlation and heteroskedasticity.

[27] In practice, we calculate individual turnover as follows. We sum up of the absolute values of the changes in allocations across all funds for each trade and we divide this sum by two. The change is calculated with respect to the *actual* allocations before the trade.

[28] Note, though, that there is a sense in which even the limited turnover in our sample can be viewed as substantial, if not excessive. If we consider turnover only for those participant/year observations where at least one trade did take place, we obtain an average annual figure of 130 percent. In other words, the individuals in our sample trade infrequently, but when they do, they rebalance their portfolio by substantial amounts. We thank Shlomo Benartzi for suggesting this point.

that turnover increases with a participant's salary. Turnover also increases with age, with the exception of the 65+ group, and with job seniority.

III. Regression Analysis

The regression analysis relates asset allocation choices and trading activity to common effects and participants' characteristics. The constant and time-varying common effects are captured by a constant and four year dummies for the years 1995, 1996, 1997, and 1998 (these are indicator variables that for each participant equal one in a particular year, zero otherwise). We then consider demographic and earnings characteristics. The following participant's characteristics are constant over time:

- "Male": indicator variable equal to one if the participant is male, zero otherwise;
- "Married": indicator variable equal to one if the participant is married, zero otherwise, as of August 1998;
- "Married*Male": indicator variable equal to one if the participant is married *and* male, zero otherwise;
- "Salary": 1997 annual salary, as of October 1997 (unit: ten thousand dollars);
- "Pre-94": indicator variable equal to one if the participant was in the plan before April 1994, zero otherwise.

A second set of participants' characteristics varies over time:

- "Age": age of the participant as of year of observation (unit: years);
- "Time Employed": time the participant has been with the company as of year of the observation (unit: years).

The explanatory variables above essentially correspond to the criteria used to sort observations in the panel data set in the previous section. Note that since some observations for some of the explanatory variables are missing, we have to further reduce our sample. In the regressions, we follow 6,023 participants (N) for an average of 4.4 years (T-bar), for a total of 26,722 observations.

A. *Average Equity Allocations*

We relate average annual equity allocations to the explanatory variables listed above. Since equity allocations are restricted to be between zero and one, we use a *censored regression* model. Let $s_{i,t}$ denote the percentage allocation to equities. We assume

(1)

$$s_{i,t} = \mathbf{x}_t'\boldsymbol{\beta} + \mathbf{y}_i'\boldsymbol{\gamma} + \mathbf{z}_{i,t}'\boldsymbol{\delta} + \varepsilon_{i,t}, \text{ if } 0 < s_{i,t} < 1;$$

$$s_{i,t} = 0, \text{ if } \mathbf{x}_t'\boldsymbol{\beta} + \mathbf{y}_i'\boldsymbol{\gamma} + \mathbf{z}_{i,t}'\boldsymbol{\delta} + \varepsilon_{i,t} \leq 0;$$

$$s_{i,t} = 1, \text{ if } \mathbf{x}_t'\boldsymbol{\beta} + \mathbf{y}_i'\boldsymbol{\gamma} + \mathbf{z}_{i,t}'\boldsymbol{\delta} + \varepsilon_{i,t} \geq 1.$$

$\mathbf{x}_t$ is the vector of realizations of the explanatory variables which are common to all participants (constant and year dummies); $\mathbf{y}_i$ is the vector of *constant* participants' characteristics (gender, marital status, salary, time of entry); $\mathbf{z}_{i,t}$ is the vector of realizations of *time-varying* participants' characteristics (age and seniority); $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$ are conforming vectors of coefficients; $\varepsilon_{i,t}$ is a normally distributed error term.

Note that our approach in estimating the demand function for equities differs from that of Ameriks and Zeldes (2000) in several respects. First, Ameriks and Zeldes estimate two separate demand function models: A probit selection model describes the probability of equity ownership, while a linear model describes equity shares conditional on ownership. In our approach, we model jointly the decision of holding equities and the decision of how much equity to hold. This seems more appropriate since the same variables determine whether to hold equities and how much equities to hold. Second, Ameriks and Zeldes estimate fixed-effects models, hence leaving the constant heterogeneity across participants unexplained. Since our data set has information on participants' characteristics in addition to age, we explicitly model the heterogeneity in terms of the variables y_i. Third, the two panel data sets considered by Ameriks and Zeldes cover longer time periods than our sample. This creates an identification problem between cohort and time effects, and hence creates the need to separately estimate a model with age and time effects and a model with age and cohort effects. Since our panel covers only a period of roughly four years, it is more natural to estimate and interpret models with age and time effects only.

Results of the regressions are presented in Table 6. The model shows a low pseudo-R^2 of 4.19 percent, but the joint significance of the explanatory variables is high. The high number of censored observations (roughly 12,000 left-censored and 8,500 right-censored) confirms the appropriateness of the censored regression model. In the following, we discuss the significant effects that we document.[29]

The year dummies, all significant, show an upward trend in equity allocations, confirming the findings of Table 3. Male participants invest more in equities than their female counterparts: 19.13 percent more. This effect is consistent with the summary-statistics evidence in Table 3 and confirms the results of other authors. Hinz et al. (1997), for example, find that women invest more conservatively than men, after controlling for other demographic characteristics, using data from the Federal Government's Thrift Savings Plan. Similar findings are noted by Bajtelsmit and VanDerhei (1997), who use data from one large 401(k) plan, and by Sundén and Surette (1998), who use data from the 1992 and 1995 SCF.[30] Married participants also invest more in equities: the difference in allocations relative to their single counterparts is 14.44 percent. Salary increases the equity allocation by 1.77 percent for each $10,000 of extra income. This effect confirms the pattern documented by Bodie and Crane (1997) on the basis of summary statistics for different net wealth groups.

Having entered the plan before April 1994 reduces the equity allocation by 31.92 percent. As we noted earlier, participants who were in the plan before April 1994 maintained their all-GIC allocation unless they submitted a trade to change it. Hence, the pre-94 effect hints at a substantial inertia in revising asset allocations.

Age has a negative effect on the share held in equities: each extra year translates into a lower

TABLE 6—CENSORED REGRESSION: EQUITY ALLOCATIONS

Dependent variable	Equity allocations
Constant	−0.2935
	(−2.813)
1995	0.0460
	(4.759)
1996	0.2968
	(18.176)
1997	0.5021
	(23.815)
1998	0.6886
	(27.843)
Male	0.1913
	(2.737)
Married	0.1444
	(2.071)
Married*Male	−0.0255
	(−0.305)
Salary	0.0177
	(2.543)
Pre-1994	−0.3192
	(−5.726)
Age	−0.0093
	(−3.796)
Time Employed	0.0527
	(10.538)
$\chi^2(11)$	1,840.93
Pseudo-R^2	0.0419
Observations	26,722
Left-censored	12,041
Uncensored	8,569
Right-censored	6,112
T-bar	4.4
N	6,023

Notes: The table presents results of a censored regression of annual average equity allocations against time effects and participants' characteristics. "1995," "1996," "1997," and "1998" are year dummy variables. "Male" is a dummy variable equal to one if the participant is male, zero otherwise. "Married" is a dummy variable equal to one if the participant is married, zero otherwise. "Married*Male" is a dummy variable equal to one if the participant is married *and* male, zero otherwise. "Salary" is the annual 1997 salary (unit: ten thousand dollars). "Pre-1994" is a dummy variable equal to one if the participant entered the plan before 1994, zero otherwise. "Age" is the age of the participant as of the year of the observation (unit: years). "Time Employed" is the time participant has been employed as of the year of the observation (unit: years). T-ratios, reported in parentheses, are adjusted for serial correlation and heteroskedasticity. The pseudo-R^2 is the log-likelihood value on a scale from zero to one, where zero corresponds to the constant-only model and one corresponds to perfect prediction (a log-likelihood of zero).

[29] As mentioned above, by (marginally) significant we denote a coefficient different from zero at the (5-percent) 1-percent level in a two-sided test, which corresponds to a critical value of $(\pm 1.96) \pm 2.58$ for the t-ratio.

[30] Wilbur G. Lewellen et al. (1977) report similar results for a sample of brokerage accounts.

allocation to stocks by 93 basis points.[31] This is remarkably close to the practitioners' rule of thumb of decreasing one's equity exposure by 1 percent for each additional year of age. Seniority on the job has a separate and opposite effect relative to age: one more year with the company leads to an extra 5.27 percent allocated to equities. This is consistent with the notion that higher job security makes an investor's human capital safer, and this can be compensated for by a higher allocation to equities.

B. *Annual Number of Trades*

Let $n_{i,t}$ denote the number of annual trades by the individual i in year t. Since this dependent variable is a count variable, we implement a negative binomial regression model. The negative binomial model is a variation of the Poisson model, where the Poisson parameter is assumed to be itself drawn from a Gamma distribution. The negative binomial model encompasses the Poisson model as a special case, and allows for more dispersion than the Poisson distribution. Specifically, we have

(2)

$$\mathrm{pr}(n_{i,t}) = \int_0^\infty \frac{1}{n_{i,t}!} e^{-\lambda_{i,t}} \lambda_{i,t} \, dF(\lambda_{i,t}; \phi_{i,t}, \eta).$$

Hence, the probability density of observing $n_{i,t}$ annual trades equals the expectation of a Poisson density with parameter $\lambda_{i,t}$, where the parameter $\lambda_{i,t}$ is distributed following a Gamma distribution $F(\lambda_{i,t}; \phi_{i,t}, \eta)$. The first parameter of the Gamma distribution is modeled as a function of the explanatory variables $\mathbf{x}_t$, $\mathbf{y}_i$, and $\mathbf{z}_{i,t}$. Namely, we have

$$\phi_{i,t} = e^{\mathbf{x}_t'\beta + \mathbf{y}_i'\gamma + \mathbf{z}_{i,t}'\boldsymbol{\delta}}. \tag{3}$$

Hence, the Poisson parameter $\lambda_{i,t}$ has expectation $E(\lambda_{i,t}) = \phi_{i,t}/\eta$ and variance $V(\lambda_{i,t}) = \phi_{i,t}/\eta^2$, while the annual number of trades has expectation $E(n_{i,t}) = \phi_{i,t}/\eta$ and variance $V(n_{i,t}) = \phi_{i,t}(1 + \eta)/\eta^2$. Therefore, the variance-to-mean ratio of the negative binomial equals $(1 + \eta)/\eta$: the negative binomial specification allows for overdispersion, with the original Poisson a limiting case as $\eta \uparrow \infty$. The parameter vectors β, γ, and $\boldsymbol{\delta}$ are the partial derivatives of the log of the number of trades predicted by the model with respect to the explanatory variables. For further discussion of the negative binomial model, see Jerry Hausman et al. (1984).[32]

Results of the negative binomial regression are presented in Table 7. While the fit of the regression is a low 2.8 percent pseudo-R^2, the explanatory variables are strongly jointly significant. The regression model shows an overall positive trend in trading activity over the years, confirming the summary-statistics evidence of Table 4. In addition, being male has a (marginally) significant and positive effect on the number of trades. A single male participant trades roughly 30 percent more than a single female participant. Salary has a small, but significant impact on trading activity: a salary increase of \$10,000 increases trading by about 2.3 percent. Age has a small but significant effect: one more year of age increases trading by 1.4 percent. Finally, time employed has a stronger and significant effect. One more year of employment increases trading by about 7 percent.

The effects documented above qualify and complement the patterns identified in the discussion of the summary statistics. In particular, we find that being married, while still having a positive impact, is now insignificant.

C. *Annual Portfolio Turnover*

Let $v_{i,t}$ denote the annual turnover of participant i in year t. We model turnover as a linear

[31] We also estimated a specification including both age and age squared, to capture possible nonmonotonicities in the relation between equity allocations and age. The coefficients on the two terms, both significant, are such that the equity allocation implied by the model peaks very early, at 32.5 years of age. Hence, the overall negative association between equity allocations and age from the linear model is confirmed by a nonlinear specification.

[32] We also estimated a Poisson regression model, although the null of a Poisson distribution is strongly rejected in our sample. The estimates from the Poisson models are very close to those obtained with the negative binomial model, both in magnitude and significance.

TABLE 7—NEGATIVE-BINOMIAL REGRESSION: NUMBER OF TRADES

Dependent variable	Number of trades
Constant	−8.6924
	(−50.058)
1995	0.2543
	(4.673)
1996	0.3595
	(6.116)
1997	0.5195
	(8.428)
1998	0.4965
	(7.519)
Male	0.2827
	(2.359)
Married	0.1520
	(1.283)
Married*Male	−0.0844
	(−0.600)
Salary	0.0225
	(11.734)
Pre-1994	−0.5832
	(−6.748)
Age	0.0142
	(3.718)
Time Employed	0.0693
	(8.611)
$\chi^2(11)$	717.28
Pseudo-R^2	0.0280
Observations	26,722
T-bar	4.4
N	6,023

Notes: The table presents results of a negative binomial regression of the annual number of trades against time effects and participants' characteristics. "1995," "1996," "1997," and "1998" are year dummy variables. "Male" is a dummy variable equal to one if the participant is male, zero otherwise. "Married" is a dummy variable equal to one if the participant is married, zero otherwise. "Married*Male" is a dummy variable equal to one if the participant is married *and* male, zero otherwise. "Salary" is the annual 1997 salary (unit: ten thousand dollars). "Pre-1994" is a dummy variable equal to one if the participant entered the plan before 1994, zero otherwise. "Age" is the age of the participant as of the year of the observation (unit: years). "Time Employed" is the time participant has been employed as of the year of the observation (unit: years). T-ratios, reported in parentheses, are adjusted for serial correlation and heteroskedasticity. The pseudo-R^2 is the log-likelihood value on a scale from zero to one, where zero corresponds to the constant-only model and one corresponds to perfect prediction (a log-likelihood of zero).

function of the explanatory variables, as long as turnover is strictly positive. This is again a censored regression model where

$$(4) \quad v_{i,t} = \mathbf{x}_t'\boldsymbol{\beta} + \mathbf{y}_i'\boldsymbol{\gamma} + \mathbf{z}_{i,t}'\boldsymbol{\delta} + \varepsilon_{i,t}$$

$$\text{if } v_{i,t} > 0, \text{ and } v_{i,t} = 0 \text{ otherwise.}$$

The error term is normally distributed. Table 8 presents estimation results for the model in (4).

The pseudo-R^2 is 3.02 percent and the explanatory variables are strongly jointly significant. As with the number of trades, we find evidence of an overall increase in trading activity for the first four years of our sample. Male has again a positive and (marginally) significant effect: annual turnover is higher by 50 percent for males than it is for females. An increase in salary by \$10,000, increases turnover by 7.19 percent. As with number of trades, having entered the plan before April 1994 reduces trading activity. In this case the effect is quite strong: −91.88 percent. Finally, age and seniority on the job increase turnover by 2.17 percent and 11.55 percent, respectively, for each additional year.

IV. The Timing of Changes in Equity Allocations

In this section, we study the timing of changes in equity allocations, to determine whether the investors in our sample are reacting to contemporaneous and lagged returns on their equity portfolios (feedback trading), and whether they are able to successfully anticipate future market movements (market timing). In particular, we want to determine whether investors take advantage of the wildcard option in mutual fund shares (explained later in this section), documented by Chalmers et al. (1999). We perform our analysis both for the aggregate sample of all plan participants, and for three subsamples of participants.

A. *Aggregate Evidence*

We perform two types of tests of trading patterns. The first test is based on the correlation properties of equity returns and changes in equity allocations. The second test is based on the frequency of purchases and sales of equities. Both tests are performed on a daily data set of changes in equity allocations and returns on equity portfolios. To measure the overall flows of funds in and out the equity funds, we calcu-

TABLE 8—CENSORED REGRESSION: PORTFOLIO TURNOVER

Dependent variable	Turnover
Constant	−6.2677
	(−14.605)
1995	0.7272
	(7.801)
1996	0.9339
	(9.291)
1997	1.2286
	(10.961)
1998	0.6777
	(6.060)
Male	0.4977
	(2.479)
Married	0.2293
	(1.171)
Married*Male	−0.1642
	(−0.695)
Salary	0.0719
	(4.293)
Pre-1994	−0.9188
	(−6.148)
Age	0.0217
	(3.135)
Time employed	0.1155
	(7.180)
$\chi^2(11)$	235.35
Pseudo-R^2	0.0302
Observations	26,722
Left-censored	23,233
Uncensored	3,489
T-bar	4.4
N	6,023

Notes: The table presents results of a censored regression of annual portfolio turnover against time effects and participants' characteristics. "1995," "1996," "1997," and "1998" are year dummy variables. "Male" is a dummy variable equal to one if the participant is male, zero otherwise. "Married" is a dummy variable equal to one if the participant is married, zero otherwise. "Married*Male" is a dummy variable equal to one if the participant is married *and* male, zero otherwise. "Salary" is the annual 1997 salary (unit: ten thousand dollars). "Pre-1994" is a dummy variable equal to one if the participant entered the plan before 1994, zero otherwise. "Age" is the age of the participant as of the year of the observation (unit: years). "Time Employed" is the time participant has been employed as of the year of the observation (unit: years). T-ratios, reported in parentheses, are adjusted for serial correlation and heteroskedasticity. The pseudo-R^2 is the log-likelihood value on a scale from zero to one, where zero corresponds to the constant-only model and one corresponds to perfect prediction (a log-likelihood of zero).

late the change in the *average* desired allocation to equities among all the individuals in the plan on a given day. The daily equity return is the weighted average of the returns on the three basic equity funds, where the weights are the average percentage allocations across plan participants at the beginning of the month. This data set contains 1,152 daily observations for the April 1994–August 1998 period.

1. *Correlations.*—Let $\Delta\bar{s}_t^*$ denote the change in the cross-sectional average desired equity allocation between day $t-1$ and day t, and let $\bar{r}_t$ denote the cross-sectional average return on the participants' equity portfolio during the same period. We calculate autocorrelation coefficients, $\rho(\Delta\bar{s}_t^*, \Delta\bar{s}_{t-k}^*)$ and $\rho(\bar{r}_t, \bar{r}_{t-k})$, and cross-correlation coefficients $\rho(\Delta s_t^*, \bar{r}_{t-k})$. Estimates are reported in Panel A of Table 9. We find that equity returns display some positive serial correlation: the autocorrelation coefficient at the one-day lag (Lag 1) is a significant and substantial 0.22, but correlation coefficients at all other lags are insignificant and take mainly negative values. As argued by Gregory B. Kadlec and Douglas M. Patterson (1999), more than 50 percent of the positive autocorrelation in portfolio returns could be due to the effect of stale pricing: fund shares are marked to market based on the closing prices of the underlying equities. Closing prices are, in turn, almost always the price of the last trade in the stock. For infrequently traded stocks, this tends to increase the persistence in prices, and hence generates positive serial correlation in returns. This apparent persistence in prices is lost as soon as the stock is traded again and it is marked to market with the transaction. Hence the quick decay in the autocorrelation of equity fund returns.

Changes in equity allocations also display positive serial correlation. In particular, at a one-day lag (Lag 1) the correlation is a significant 0.27. Autocorrelation coefficients at longer lags, while still overall positive and significant, are much smaller. This persistence in allocation changes is consistent with the notion that some participants react immediately to news, while other participants react with one or more days of delay.

Note that the autocorrelation in individual stock returns induced by stale prices is essentially an illusion: attempts to trade the stale-priced stocks are likely to refresh the asset's price to its appropriate level. In the case of mutual fund shares, on the other hand, the

TABLE 9—EQUITY ALLOCATIONS AND EQUITY PORTFOLIO RETURNS: AGGREGATE EVIDENCE

Panel A: Correlations

Autocorrelation of equity returns

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
0.2236	0.0391	−0.0278	−0.0065	−0.0371	0.0143	−0.0483
(4.096)	(−0.885)	(−0.658)	(−0.164)	(−0.890)	(0.385)	(−1.356)

Autocorrelation of changes in allocations

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
0.2722	0.0856	0.0993	0.1225	0.0924	0.0881	0.0852
(4.356)	(1.837)	(2.586)	(3.807)	(2.218)	(2.384)	(2.591)

Cross-correlation of allocations and lead and lagged returns

Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3
0.0001	−0.0113	−0.0735	0.1233	0.3088	0.1341	0.0344
(0.004)	(−0.339)	(−1.769)	(1.931)	(6.369)	(2.320)	(0.817)

Panel B: Conditional and Unconditional Trade Frequencies

	Purchase	Sale
After "up" day	58.36**	31.76**
After "down" day	45.51**	46.12**
All days	52.87	37.91

Notes: The table presents evidence of the time-series properties of changes in overall average equity allocations and equity returns at the daily frequency. Panel A reports the autocorrelations of the changes in equity allocations and the cross-correlations between allocation changes and equity returns. T-ratios, in parentheses, are adjusted for heteroskedasticity. Panel B reports the frequency of purchases and sales in the days following up-market days and down-market days, and in the entire sample. We compare the conditional trade frequencies to the unconditional frequencies based on the critical values from the binomial distribution. One (two) asterisk(s) denote rejection of the null of random trading in a one-sided test at the 5-percent (1-percent) significance level.

readjustment effect associated with trading does not occur. In fact, Chalmers et al. (1999) argue that mutual funds provide their shareholders with a valuable wildcard option. In our plan, for example, all transactions completed by 4:00 P.M. EST receive that day's closing prices.[33]

If investors take advantage of this option, we should see a strong positive contemporaneous correlation between changes in equity allocations and equity returns. In other words, if investors know that equity returns are positively correlated, they should take advantage of this effect by increasing (decreasing) their equity exposure when returns are high (low).

We can test this proposition by looking at the cross-correlation coefficients between allocations and returns. The results are presented in the third subpanel of Table 9. We find that changes in equity allocations correlate positively with contemporaneous returns (Lead 0), but the correlation is small, 0.12, and (almost) marginally significant. On the other hand, there is a strong and significant correlation between allocations and returns at a one-day lag (Lag 1): 0.31. The correlation at a two-day lag is marginally significant and positive, 0.13. Since the

[33] The international funds prices reflect the closing prices of the international markets, but also reflect the currency conversion at 4:00 P.M. EST.

autocorrelation of equity returns dies off very quickly, this lagged response of allocations to returns does not generate profits. Hence, our investors react with a lag to market developments and take little, if any, advantage of the wildcard option offered by mutual funds. These findings are consistent with Chalmers et al. (1999), who study flows in over 1,000 U.S. mutual funds during the 1998–1999 period.

As a second test of the investing ability of our investors, we examine the correlations between current equity allocation changes and equity returns over the next few days. If investors are successful market-timers, the correlations should be positive. The cross-correlations at lead 1 and 2 reported in Table 9 are negative, small, and insignificant. The cross-correlation at lead 3 is essentially zero. This suggests that investors are not successful market-timers.

2. *Conditional and Unconditional Trade Frequencies.*—The correlation patterns documented above suggest that our plan participants are *lagged, positive feedback traders;* i.e., they react positively, with a one-day lag, to market returns. We now want to further determine whether these lagged reactions to market developments were likely to happen by chance, given random trading.[34]

Positive feedback traders should purchase (sell) shares after a market rise (fall) more frequently than one would expect given a random distribution of share purchases (sales) of the same number within the sample period. Similarly, we would expect positive feedback traders to sell (purchase) shares following days after a market rise (fall) less frequently than one would expect given a random distribution of share sales (purchases). In both cases, the null hypothesis is that the frequency of purchase days (sale days), conditional on the previous day's market direction, is equal to the unconditional frequency.

As an example, consider the case where we compare the frequency of purchases after up-market days to the unconditional frequency of purchases. Purchases are defined here as *increases* in the average desired equity allocation, and up-market days are days for which the rate of return on the equity index is positive. Let d denote the total number of trading days and let d_u denote the number of up-market days. Let pu denote the total number of purchases and let pu_u denote the number of purchases following an up-market day. Under the null of no-feedback trading, purchases after up-market days are just as likely as during any other day, and hence they are drawn from the same distribution. Hence, under the null, the distribution of pu_u is a binomial with parameters d_u and $pu/d \equiv q_p$:

(5)

$$\Pr(pu_u = k) = \frac{d_u!}{k!(d_u - k)!}(q_p)^k(1 - q_p)^{d_u - k}.$$

Given the realized value of pu_u, we can determine whether it falls above the critical values for the binomial distribution. This, in turn, allows us to determine whether the conditional frequency of purchases, pu_u/d_u, is significantly higher than the unconditional frequency of purchases, pu/d.[35]

Relative to the examination of cross-correlation coefficients, the test described above has two main advantages. First, we are not imposing linearity in the relation between changes in equity allocations and equity returns. In addition, we are able to study the relation between changes in equity allocations and returns, separately for up-market and down-market days, and separately for purchases and sales. Second, the comparison of conditional and unconditional trade frequencies should be less sensitive to outliers, since the *magnitude* of changes in equity allocations does not matter, but only their sign does. Results are reported in Panel B of Table 9.

The results support the notion that investors in our sample are, on average, positive feedback traders. The frequency of purchases after an up-market day is 58.36 percent and the frequency of sales after a down-market day is

[34] We performed similar comparisons of trading frequencies, where the conditioning event is the *contemporaneous,* rather than the one-day lagged equity return. These results are not reported since we never were able to reject the null of random trading.

[35] William N. Goetzmann and Massimo Massa (1999) implement this same test to identify positive feedback and contrarian traders, within a sample of index fund investors.

46.12 percent. These frequencies are significantly greater than the unconditional frequencies of purchases and sales, 52.87 percent and 37.91 percent, respectively.[36] The frequency of purchases after a down-market day is 45.51 percent and the frequency of sales after a down day is 31.76 percent. Both these frequencies are significantly lower than the unconditional frequencies of purchases and sales.

B. *Disaggregated Evidence*

The analysis discussed above gives us a picture of how our plan participants behave in the aggregate. Yet, it is useful to further investigate the data at the disaggregated level, to examine why people trade when they do. For example, it is possible that only a small number of individuals are exercising the wildcard option or are able to time the market. These participants are likely to be among the most active traders and/or the participants with the highest *ex post* returns.

Therefore, we constructed three subsamples of participants. First, among the 4,783 participants present throughout the sample, we select the top 10 percent (478 participants) in terms of their average annual number of trades, the "active" participants. Second, we select the top 10 percent (478) participants in terms of the realized average annual portfolio returns, the "successful" participants. Third, we select those participants who belong to *both* samples, the "active and successful" participants (108).[37]

To have an idea of the trading activity of the participants in the three samples, we calculated the average total number of trades during the April 1994–August 1998 period. The "active" traders rebalanced an average of 8.14 times. The successful traders rebalanced an average of 2.72 times. The "active and successful" traders rebalanced an average of 8.79 times. These statistics should be compared to the average total number of trades of all the participants in the plan for the entire period, 1.19.

For each of the three samples, we calculate the daily change in the average desired equity allocation and equity returns.[38] We then document the time-series properties of these changes in equity allocation for these three samples as we did for the aggregate sample.

1. *Correlations.*—Correlations are reported in Panel A of Table 10.[39] The first subpanel presents results for the "active" participants. Not surprisingly, we find that the time-series patterns of allocations for the active participants mimic those found in the aggregate: serial correlation is positive and significant at one lag; cross-correlations with equity returns are positive and significant at one lag and positive and marginally significant contemporaneously. This similarity is to be expected, since the trading activity of the most active participants is driving the overall trading activity.[40]

The second subpanel presents results for the "successful" participants. Interestingly, the time-series patterns of allocations for this group are very different: their allocation changes are not

[36] The fact that the unconditional frequency of purchases is higher than that of sales is consistent with the evidence from Table 5, showing an overall increase in average equity allocations during the five years of the sample. Also, note that the frequencies of purchases and sales do not sum to one because during some days the overall allocation to equities did not change.

[37] Portfolio returns are returns on the total portfolio held by investors, including both equities and GIC. Average annual returns are 10.16 percent for the "active" participants, 14.14 percent for the "successful" participants, and 14.31 percent for the "active and successful" participants. These statistics should be compared to the average 8.62 percent return for all the participants in the plan the entire time.

[38] For each group, we constructed an equity index based on the average percentage allocations across the participants in that group at the beginning of the month.

[39] The table does not report autocorrelation coefficients for the returns in the equity indices corresponding to the different groups, since they closely mimic those estimated at the aggregate level.

[40] To further focus our analysis on active traders, we also formed a sample of participants who, at least during one year, traded more than ten times (they correspond to the top 0.19 percent of the distribution of annual number of trades reported in Table 4). This is a group of 36 individuals who traded an average of 28.69 times during the sample period, and realized an average annual portfolio return of 11.04 percent. Time-series patterns for this group are somewhat different from the aggregate: autocorrelations in allocation changes are not significant; and among cross-correlations, the contemporaneous one, 0.08, is marginally significant, while all the others are insignificant. Hence, even this group of very active traders responds only weakly to contemporaneous returns. We also tested for lagged feedback trading by comparing conditional and unconditional trade frequencies. The results of these tests were not significant.

TABLE 10—EQUITY ALLOCATIONS AND EQUITY PORTFOLIO RETURNS: DISAGGREGATED EVIDENCE

Panel A: Correlations

Active participants

Autocorrelation of changes in allocations

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
0.1677	0.0196	0.0152	0.0191	0.0378	−0.0018	0.0462
(4.811)	(0.465)	(0.396)	(0.616)	(0.972)	(−0.053)	(1.336)

Cross-correlation of allocations and lead and lagged returns

Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3
−0.0063	−0.0294	−0.0553	0.1094	0.2584	0.0701	0.0074
(−0.197)	(−0.928)	(−1.271)	(2.056)	(5.537)	(1.357)	(0.205)

Successful participants

Autocorrelation of changes in allocations

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
0.0630	−0.0061	0.0079	0.0559	0.0438	0.0263	0.0188
(1.646)	(−0.165)	(0.221)	(1.676)	(1.006)	(0.751)	(0.556)

Cross-correlation of allocations and lead and lagged returns

Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3
0.0088	0.0541	0.0173	0.0354	0.0934	0.0521	0.0292
(0.295)	(1.842)	(0.498)	(1.100)	(1.872)	(1.622)	(0.939)

Active and successful participants

Autocorrelation of changes in allocations

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
0.0297	−0.0324	−0.0372	0.0307	−0.0196	−0.0042	−0.0081
(0.875)	(−0.860)	(−1.022)	(1.056)	(−0.530)	(−0.152)	(−0.245)

Cross-correlation of allocations and lead and lagged returns

Lead 3	Lead 2	Lead 1	Lead 0	Lag 1	Lag 2	Lag 3
−0.0011	0.0418	0.0081	0.0590	0.0311	0.0257	0.0068
(−0.036)	(1.305)	(0.231)	(1.406)	(0.435)	(0.791)	(0.199)

Panel B: Conditional and Unconditional Trade Frequencies

Active participants

	Purchase	Sale
After "up" day	48.02*	35.67
After "down" day	40.24*	42.28*
All days	44.70	38.52

Successful participants

	Purchase	Sale
After "up" day	28.48	20.76
After "down" day	22.13*	22.34
All days	25.74	21.48

TABLE 10—*Continued.*

Panel B: Conditional and Unconditional Trade Frequencies—*Continued.*
Active and successful participants

	Purchase	Sale
After "up" day	23.74	19.75
After "down" day	18.79	19.39
All days	21.57	19.65

Notes: The table presents evidence of the time-series properties of changes in average equity allocations and equity returns at the daily frequency, for three subsamples of participants who are present in the plan the entire time. "Active participants" refers to the top 10 percent of the participants in number of trades; "Successful participants" refers to the top 10 percent of the participants in *ex post* portfolio returns; "Active and successful participants" are the participants who belong to both groups. Panel A reports the autocorrelations of the changes in equity allocations and the cross-correlations between allocation changes and equity returns. T-ratios, in parentheses, are adjusted for heteroskedasticity. Panel B reports the frequency of purchases and sales in the days following up-market days and down-market days, and in the entire sample. We compare the conditional trade frequencies to the unconditional frequencies based on the critical values from the binomial distribution. One (two) asterisk(s) denote rejection of the null of random trading in a one-sided test at the 5-percent (1-percent) significance level.

significantly serially correlated, nor do they correlate significantly with equity returns at any lead or lag. Hence, it appears that successful investors do not owe their success to the exploitation of the wildcard option or to market-timing ability.

The third subpanel panel presents results for the "active and successful" participants. As with the "successful" participants, neither the autocorrelations of allocation changes, nor the cross-correlations between allocation changes and returns are significant. Hence, these participants who are both active and successful, do not respond to nor anticipate market returns.

2. *Conditional and Unconditional Trading Frequencies.*—As with our analysis of the aggregate sample, we next study the conditional frequencies of purchases and sales, and compare them to the unconditional frequencies. Results are reported in Panel B of Table 10.

The patterns are similar to those documented by the correlation tests. We have some (marginally) significant evidence of positive feedback trading for the "active" traders. For the other two groups, the differences between conditional and unconditional frequencies are, in all but one case, insignificant. Hence, based on the comparison of conditional and unconditional trade frequencies, one cannot rule out the null that the trading patterns of the "successful" and the "active and successful" participants were simply a result of random trading.

V. Conclusions

This paper examines a new data set documenting the allocations and trading activity of a large number of participants in a 401(k) plan. Plan participants tend to cluster their equity allocations around zero and 100 percent, rebalance their portfolio infrequently, and tend to maintain their default asset allocation choice, when given one.

Some patterns of portfolio choice and trading activity by marital status, salary, and job seniority are broadly consistent with the implications of models of rational choice.

Regression analysis shows how asset allocations and trading activity vary with demographics and other participants' characteristics: Men invest more in equities and trade more frequently than women. Married investors invest more aggressively than their single counterparts. A higher salary leads to higher equity allocations and more active trading. Entering the plan with a default allocation of 100 percent to the risk-free asset leads to lower average allocations to equities and less intense portfolio reshuffling. Age makes investors more "cautious" in their allocations. Older participants also trade more frequently than their younger counterparts.

Tests based on daily data show that, on average, investors in our sample tend to react with a one-day lag to market developments, take little, if any, advantage of the wildcard option in equity-fund shares, and are not able to time the market. Interestingly, participants who realize the highest portfolio returns do not respond to nor anticipate returns at any lead or lag.

APPENDIX

The robust estimator of the covariance matrix of the estimates is William H. Rogers' (1993) extension of Peter J. Huber's (1967) formula. This estimator is robust to both heteroskedasticity and clustered sampling. The estimator has the form

$$\text{(A1)} \qquad \mathbf{V}\left(\sum_{i=1}^{N} \mathbf{u}_i'\mathbf{u}_i\right)\mathbf{V},$$

where $\mathbf{V}$ is minus the inverse of the hessian of the log-likelihood (the conventional estimator) and $\mathbf{u}_i \equiv \sum_{t=1}^{T_i} \partial \ln L_{i,t}/\partial \boldsymbol{\delta}$ (where $L_{i,t}$ is the likelihood of the t-th observation for individual i and $\boldsymbol{\delta}$ is the parameter vector) is the vector of contributions of the *group* of T_i observations of individual i to the scores of the likelihood.

As an example, consider the case of the linear regression model. In this case, the robust estimator of the covariance matrix of the estimates takes the form:

$$\text{(A2)} \qquad \left(\sum_{i=1}^{N}\sum_{t=1}^{T_i} \mathbf{z}_{i,t}\mathbf{z}_{i,t}'\right)^{-1} \sum_{i=1}^{N}\left(\sum_{t=1}^{T_i} \hat{\varepsilon}_{i,t}\mathbf{z}_{i,t}\right) \times \left(\sum_{t=1}^{T_i} \hat{\varepsilon}_{i,t}\mathbf{z}_{i,t}'\right) \times \left(\sum_{i=1}^{N}\sum_{t=1}^{T_i} \mathbf{z}_{i,t}\mathbf{z}_{i,t}'\right)^{-1},$$

where $\mathbf{z}_{i,t}$ is the vector of observations on the explanatory variables and $\hat{\varepsilon}_{i,t}$ is the residual of the regression. Monte Carlo evidence for the linear regression model shows that the correction for clustering works well as long as the largest cluster is 5 percent or less of the total sample (Rogers, 1993). This condition is easily satisfied in our analysis, where the smallest total number of observations is 26,722, and the largest cluster is five yearly observations (0.019 percent of the total).

The expression in equation (A2) can be contrasted with the standard adjustment for heteroskedasticity and serial correlation in time-series models (see, for example, Lars P. Hansen and Robert J. Hodrick, 1980; and see Whitney Newey and Kenneth D. West, 1987, for the correction to ensure positive definiteness):

$$\text{(A3)} \qquad \left(\sum_{t=1}^{T} \mathbf{x}_t\mathbf{x}_t'\right)^{-1} \sum_{t=1}^{T}\sum_{k=-K}^{K} \hat{\varepsilon}_t\hat{\varepsilon}_{t-k}\mathbf{x}_t\mathbf{x}_{t-k}' \times \left(\sum_{t=1}^{T} \mathbf{x}_t\mathbf{x}_t'\right)^{-1},$$

where $\mathbf{x}_t$ is the vector of explanatory variables, $\hat{\varepsilon}_t$ is the residual, and K is the number of non-zero autocorrelations.

Robust estimates of coefficient standard errors based on (A1) can be implemented in the statistical package STATA invoking the "cluster" option within the "robust" option, in both least-squares regression and maximum-likelihood estimation.

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