What is the Impact of Financial Advisors on Retirement Portfolio Choices and Outcomes?*

John Chalmers
Lundquist College of Business
University of Oregon
Eugene, OR 97403-1208
jchalmer@uoregon.edu

Jonathan Reuter
Carroll School of Management
Boston College and NBER
Chestnut Hill, MA 02467
and NBER
reuterj@bc.edu

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ABSTRACT

We study retirement savings decisions and outcomes in Oregon University System's Optional Retirement Plan (ORP). During our sample period, 32% of ORP participants choose to invest through HIGH, which markets itself as providing personal face-to-face financial service. The other participants choose to invest through three lower-service providers, with 51% investing through LOW. Consistent with lower levels of financial literacy driving demand for financial advisors, we find that younger, less highly educated, and less highly paid employees are more likely to invest through HIGH. When we compare the investment strategies and performance of HIGH and LOW investors, several differences emerge. Consistent with financial advisors impacting asset allocation, HIGH investors allocate their retirement contributions across a larger number of investments, are less likely to remain fully invested in the default investment option, and less likely to change their equity allocation during the recent financial crisis. On the other hand, HIGH investors' portfolios are significantly riskier, and underperform by approximately 2 percent per year on a risk-adjusted basis. Although we cannot conclude that those investing through a financial advisor would have been better off investing on their own, we can conclude that access to financial advisors is a costly and imperfect substitute for financial literacy.

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I. Introduction

Lifelong financial security is a topic of great interest to policy makers and academics. The better an individual's financial decision-making, the greater her odds of achieving this security. This is especially true for individuals with defined contribution retirement plans. One way to improve the quality of financial decisions is to invest in educational programs that target financial literacy (see, for example, Bernheim, Garrett, and Maki (2001)). The natural alternative is to have financial intermediaries, like 401(k) providers, provide access to financial advice. In this paper, we study the extent to which face-to-face interactions with financial advisors help investors to overcome lower levels of financial literacy.

Providing financial advice to investors is a multi-billion dollar industry. However, given the volatility of investment returns, it can be difficult for investors to distinguish good advice from bad. Moreover, Gabaix and Laibson (2006) and Carlin (2009) argue that financial service providers can profit from transforming simple financial products into more complex products that offer little or no additional functionality. Therefore, in exchange for the fees paid to financial advisors, the recommendations that investors receive can range from helpful to harmful.

The literature assessing the efficacy of financial advice is small but growing.[1] For example, Reuter and Zitzewitz (2006) question the value of mutual fund recommendations published in personal finance publications. In the study closest to our own, Bergstresser, Chalmers and Tufano (2009) use fund-level data to evaluate the costs and benefits of purchasing mutual funds through financial advisors and brokers rather than directly from mutual fund families. Although

[1] The largest obstacle to studying the impact of financial advice has been the lack of data on a population of investors that has access to financial advice. Benartzi (2001), Benartzi and Thaler (2001), and Agnew, Balduzzi, and Sunden (2003) all study asset allocation decisions within 401(k) plans, which traditionally have not provided access to financial advisors. Similarly, Barber and Odean (2000) study the behavior of active investors who invest through a discount brokerage, a selected sample of investors who are likely to be the most comfortable making their own investment decisions.

broker-sold funds charge significantly higher fees than direct-marketed funds, holdings of broker-sold funds total approximately $2 trillion. Along the dimensions that these authors can measure—including after-fee returns—they find little evidence that brokers add value. However, because they are limited to fund-level data, they are unable to evaluate the impact of financial advice on individual decisions related to asset allocation and fund selection, or the performance of individual retirement accounts.

We study the impact of financial advisors on the individual retirement savings decisions of a large sample of public college and university employees. Our data come from the Oregon University System (OUS), which offers faculty and administrators the choice between a traditional defined benefit plan known as the Public Employees Retirement System (PERS) and a portable defined contribution plan known as the Optional Retirement Plan (ORP). Between October 1996 and October 2007, almost one-third of ORP participants choose to invest through HIGH, which provides "personal one-on-one service" but charges higher-than-normal fees. The other two-thirds of ORP participants choose to invest through three lower-service providers, the most popular of which is LOW.

Combining administrative data from Oregon University System with account-level data from HIGH and LOW allows us to answer two broad questions.[2] First, how does demand for financial advisors vary with proxies for variation in financial literacy? Second, how do the portfolios and returns of HIGH investors, who receive guidance from financial advisors, compare to those of LOW investors, who are largely self-directed? Because investors self-select into HIGH or LOW, the answer to the first question has important implications for how we interpret the answer the second question.

[2] Approximately 82.5% of ORP participants choose either HIGH or LOW. The other ORP providers, SMALL and SMALLER, were dropped on November 2007. We lack account-level data for those participants who originally invested through SMALL or SMALLER.

When we study the choice of investment provider, we find that ORP participants choosing HIGH are younger, less highly educated, and less highly paid than those choosing LOW. Because financial literacy has been shown to increase with age, educational attainment, and income, we interpret these differences as evidence that demand for financial advisors is higher when financial literacy is lower. In contrast, we find few differences related to gender or ethnicity, suggesting that these demographic characteristics capture little variation in financial literacy within our highly educated sample.

After finding that demand for financial advisors is inversely related to the level of financial literacy, we compare the portfolios of HIGH and LOW investors along several dimensions.[3] The assumption underlying each of these comparisons is that financial advisors with access to HIGH's large investment menu should be able to help their clients construct and maintain portfolios that are "at least as good" as those constructed by the average self-directed investor in LOW.

We begin by focusing on annual after-fee returns earned by HIGH and LOW investors between 1999 and 2009. Ignoring potential differences in risk, HIGH investors earn returns that are approximately one percentage point lower per year, which is what we might expect given the additional fees that HIGH investors must pay to their financial advisors. However, because the annual returns earned by HIGH investors are significantly more variable than those earned by LOW investors (with a standard deviation of 25.1% versus 20.6%), the size of the difference varies widely from year to year. When we switch from raw to risk-adjusted annual returns, HIGH investors underperform LOW investors by more than 2 percentage points per year—a difference that is both economically and statistically significant.

Turning to asset allocation and investment decisions, the evidence is mixed. On the one

[3] Because retirement contribution rates are determined by OUS and contributions are made by OUS on behalf of their employees, we cannot study the impact of financial advice on retirement savings rates.

hand, HIGH portfolios hold more funds (5.8 versus 3.6), allocated significantly more to index funds (19.7% versus 8.1%), and are less likely to remain fully invested in the default investment option (2.0% versus 9.2%). HIGH investors are also differentially less likely to adjust their allocation to domestic equity during 2008-2009, a period dominated by the recent financial crisis. Collectively, these differences suggest that (higher-fee) financial advisors help investors to pursue stable, diversified investment strategies. On the other hand, HIGH investors are just as likely as LOW investors to engage in return chasing when they allocate their initial retirement contribution across the available investments. And, more significantly, HIGH portfolios have greater loadings on market, size, book-to-market, and momentum factor loadings, suggesting greater risk taking by investors with lower average levels of financial literacy. Whether differences in portfolio risk reflect the preferences of HIGH investors or the incentives of their financial advisors is an important open question.

Because investors self-select into HIGH and LOW based on their level of financial literacy, we cannot conclude that financial-advisor guided investors in HIGH would have earned higher returns if they had managed their own portfolio in LOW. Nor can we conclude that these investors would be willing to forgo their relationship with a financial advisor in exchange for higher returns. However, the fact that the average self-directed investor outperforms the average financial advisor-guided investor provides a new estimate of the value of financial literacy.

The remainder of the paper is organized as follows. In Section II, we identify the demographic characteristics that explain the choice between HIGH and LOW. In Section III, we describe the account-level data for HIGH and LOW, and test for differences in after-fee returns, asset allocation, fund selection, and turnover. In Section IV, we summarize our findings and discuss directions for future research. In the Appendix, we provide a brief overview of the HIGH and LOW investment menus.

II. Who Demands the Service of a Financial Advisor?

A. Institutional Details

Before October 1996, employees of the Oregon University System (OUS) are automatically enrolled in Oregon's Public Employees Retirement System (PERS), the defined benefit retirement plan that covers state and local government employees. In October 1996, OUS introduces the Optional Retirement Plan (ORP), "a defined contribution, participant-directed plan that is exclusively for OUS employees".[4] At that time, existing OUS faculty and administrators are given a "one-time, irrevocable" choice between ORP and PERS.[5] Similarly, new OUS faculty and administrators must choose between ORP and PERS six months after they are hired.[6]

In this paper, we study the retirement savings choices and outcomes of OUS employees who actively choose ORP over PERS. We exploit the fact that, unlike a typical defined contribution plan, ORP participants are allowed to choose from among multiple investment providers. Between October 1996 and October 2007, ORP participants have the choice between two insurance companies (which we refer to as HIGH and LOW) and two mutual fund families (SMALL and SMALLER). From our perspective, the most important distinction between the four providers is that HIGH uses—and markets itself as using—a network of financial advisors to provide relatively *high* levels of "personal face-to-face service." In contrast, LOW, SMALL and SMALLER are more representative of investor-directed investment providers available through other defined contribution retirement plans in that they charge lower fees but provide less per-

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[4] http://www.ous.edu/dept/hr/files/Choices_Retirement_Plan_Decision-Making_Guide.pdf Ibid.
[5] Employees who converted from PERS to the ORP in 1996 may have legacy PERS benefits in addition to any ORP benefits that have accrued since 1996. While we lack data on legacy PERS benefits, for reaons discussed below, the most of our analysis focuses on OUS employees hired after January 1999.
[6] Employees who do not return their "completed OUS Retirement Plan Election Form to [their] campus Benefits Office by the 10th of the month in which [they] are eligible" are defaulted into PERS.

sonalized service.

We only possess account-level data for those participants choosing HIGH or LOW (because SMALL and SMALLER are dropped from ORP in November 2007). However, the majority of ORP participants choose to invest through these two providers. In Table 1, when we use Oregon University System payroll data to identify provider choices between October 1996 and October 2007, we see that 31.7% choose HIGH and 50.7% choose LOW.[7]

Contrasting the characteristics of those choosing HIGH versus LOW allows us to shed light on the determinants of demand for personalized service from financial advisors. As expected, we find evidence that demand for financial advisors is negatively correlated with proxies for financial literacy. Contrasting account-level data from HIGH and LOW then allows us to shed light on differences in asset allocation, turnover, and after-fee returns.[8] Because we do not know how investors choosing HIGH would have fared if they had chosen LOW, our focus is on the extent to which access to personal face-to-face service from a (financially literate) financial advisor allows investors to overcome lower levels of financial literacy.

B. Financial Advice versus Financial Guidance

The Employee Retirement Income Security Act (ERISA) prohibits defined contribution pension plan providers from giving their own financial advice on the investment options within their plans.[9] To comply with ERISA, HIGH uses algorithms developed by Ibbotson Associates to generate financial advice for investors with managed accounts. However, OUS prohibits

[7] Because OUS switched payroll systems in 1998, contribution and salary data begin in January 1999. For those joining ORP between October 1996 and January 1999, the ORP enrollment date is left censored at January 1999.

[8] Because the ORP contribution amount is set by OUS as a fixed percentage of the employee's gross salary, and is paid by OUS on behalf of the employee, we cannot study the impact of financial advice on retirement savings rates.

[9] DOL Advisory Opinion 2001-09A, also known as the The SunAmerica Opinion Letter, permits defined contribution retirement plan providers to offer financial advice only when they outsource asset allocation and investment selection decisions to independent, third party providers.

HIGH from directly managing the "participant-directed" accounts of ORP investors. Because of this restriction, it is more accurate to say that HIGH provides ORP participants with face-to-face access to financial guidance.

Fortunately, within the context of a fixed investment menu, the distinction between financial guidance and financial advice is fairly small. ERISA defines financial advice narrowly, as a recommendation that is immediately actionable. Under this definition, the recommendation to "invest 100% of your retirement assets in Vanguard's S&P 500 index fund" is *financial advice*. In contrast, the recommendation to "invest 100% of your retirement assets in a low-cost S&P 500 index fund" is *financial guidance* because the recommendation is personalized but not immediately actionable. This remains true even if the investment menu offers a single S&P 500 index fund. Therefore, while financial advisors employed by HIGH are prohibited from offering financial advice, they are allowed to offer financial guidance (and education)—a distinction that is likely lost on those seeking relationships with financial advisors.[10]

We just argued that the typical HIGH investor receives financial guidance on an ongoing basis. What about the typical LOW investor? We lack statistics on the fraction of ORP participants who seek financial guidance from LOW. However, less than 4 percent of the approximately 3 million LOW investors with a retirement account balance less than $500,000—a set that includes all but two ORP participants—choose to contact a LOW retirement consultant in any given year.

C. Participant Characteristics by Provider

Investors may value financial advisors because they have lower levels of financial literacy, derive utility from the one-on-one relationship, or both. An expanding literature links dif-

[10] A recommendations that is neither personalized nor actionable, such as "academics recommend investing in low-cost, diversified mutual funds", is classified as *financial education*.

ferences in gender, age, income, ethnicity, and education to differences in financial literacy. However, because ORP is only available to faculty and university administrators, our sample of defined contribution plan participants is unrepresentative of the general population. For example, Hispanic women with PhDs may behave differently than the Hispanic women without PhDs who have been studied in other settings. When interpreting our results, it is important to keep this caveat in mind.

In Table 2, we relate provider choice to participant salary, gender, age, ethnicity (reported for 88.5% of the participants), educational attainment at the time of employment (reported for 67.1% of the participants), and the campus at which each participant is employed. Because Table 2 is based on administrative data from OUS, we are able to include all four providers.

We calculate summary statistics in Table 2 in two ways. Consider the provider choices of female participants. In columns (2)-(5), which show the percentage of participants choosing each provider who are female, we see that 42.4 percent of participants choosing LOW and 48.0 percent of participants choosing HIGH are female. These values should be evaluated relative to the benchmark that 45.6 percent of all ORP participants are women. In columns (6)-(10), which show the distribution of female participants choosing each of the providers, we see that 47.1 percent of all female participants choose LOW and 33.4 percent choose HIGH. These values should be evaluated relative to the benchmark that 50.7 percent of all participants choose LOW and 31.7 percent choose HIGH.

Three patterns emerge from the univariate comparisons. First, the monthly salary of LOW participants is over $900 greater, on average, than that of HIGH participants. Second, demand for HIGH is substantially higher in the under-30 age group, which likely includes participants with both the longest investment horizons and the least investment experience. Third, demand for LOW increases with educational attainment. Of those participants with a Ph.D., 58.2 percent choose LOW and 26.3 percent choose HIGH. In contrast, of those participants whose highest degree is a Bachelors degree, 32.9 percent choose LOW and 43.5 percent choose HIGH. Overall, these differences suggest that—even within our relatively homogenous sample of faculty and administrators—demand for access to financial advisors falls with income, age, and education.[11] However, in contrast to studies that find lower levels of financial literacy among females and minorities (such as Lusardi and Mitchell (2007b) and Lusardi and Tufano (2008)), we find little evidence that demand for access to a financial advisor varies with gender or ethnicity.

D. Predicting Demand for Financial Advisors

To identify factors that predict demand for access to financial advisors we estimate several probit regressions. In each case, the dependent variable equals one if participant i's initial ORP retirement contribution is directed to HIGH and zero otherwise, and the sample is restricted to the 82.5% of participants who choose either HIGH or LOW. We report marginal effects, along with standard errors clustered on the month of the initial ORP retirement contribution.

We begin, in column (1) of Table 3, by focusing on salary, gender, age, and employer because these are characteristics that we observe for our full sample of ORP participants. Consistent with the univariate comparisons, we find that demand for financial advisors falls with salary, is highest for those under the age of 30 (the omitted category), and is largely uncorrelated with gender. In addition, we find that demand for HIGH is significantly lower at Oregon State University and Southern Oregon University than at University of Oregon (the omitted category). The lower demand for financial advisors at Oregon State University, which houses the engineer-

[11] Income and education are well accepted proxies for financial literacy. For example, Campbell (2006) shows that homeowners with higher income and more education are more likely to refinance their mortgage when interest rates fall. Lusardi and Tufano (2009) provide a nice, brief overview of the literature on financial literacy and retirement behavior.

ing school, is consistent with the evidence that numeracy is an important determinant of financial literacy (Lusardi and Mitchell (2007a)). Another explanation—more likely to apply to Southern Oregon University—is that across-campus differences in demand for HIGH reflect variation in the quality or accessibility of the financial advisor(s) assigned to each campus.

In column (2), we limit our sample to participants (and campuses) for which we observe data on educational attainment and ethnicity. In columns (3) and (4), we limit our sample further to participants for whom the date of the initial ORP contribution is not left censored at January 1999. One advantage of focusing on the subsample of participants for which we can observe the month of the choice between HIGH and LOW is that it eliminates noise from the age category dummy variables, and allows us to include calendar year fixed effects. A larger advantage, as we discuss below, is that it permits us to include variables that vary through time.

Looking across the columns, we continue to find that demand for HIGH falls with salary and age. We also find that it falls with educational attainment. Each of these effects is economically significant. Increasing an employee's monthly salary by one standard deviation ($2,420) reduces demand for a financial advisor by approximately 6.5 percentage points. Similarly, employees who are at least 30 years old when hired are approximately seven percentage points less likely to invest through a financial advisor. Finally, participants with PhDs are approximately 20 percentage points less likely to invest through a financial advisor. With respect to ethnicity, all of the estimated coefficients are positive (relative to the omitted category of "White"), but only the dummy variable indicating whether participant i is of Asian descent is statistically different from zero. Interestingly, in column (4), we find that demand for HIGH is 20 percentage points lower at Oregon State University and 10 percentage points lower at Oregon Institute of Technology, the two campuses at which numeracy is likely to be the highest.

In addition to providing personalized financial service, HIGH also provides access to a larger menu of investment options. For example, in October 1996, HIGH offers access to 40 different investments—four times the number of investments available through LOW. (We summarize the investment options available through HIGH and LOW in the Appendix.) To explore the possibility that demand for HIGH reflects demand for its larger investment menu, we include the ratio of the number of investment options in HIGH and LOW. This ratio ranges from a low of 3.26 to a high of 7.10. To the extent that ORP participants value access to larger investment menu, the predicted sign is positive. In contrast, the estimated coefficient is negative and statistically significant at the 5-percent level in column (3) and positive but statistically indistinguishable from zero in column (4). Between this finding and our finding that demand for HIGH is negatively correlated with proxies for financial literacy, we conclude that the typical ORP participant is choosing HIGH for access to financial advisors rather than a larger investment menu.

In columns (3) and (4), we explore the impact of recent equity market movements on the demand for a financial advisor. Our goal is to identify exogenous variation in demand for financial services. Our prediction is that demand for financial advisors will be higher when recent equity market returns have been lower or more volatile because investors will be more attuned to downside risk. The evidence is mixed. On the one hand, we find that demand for financial advisors is negatively correlated with the return on the S&P 500 index over the prior 12—even when we include calendar year fixed effects. In column (4), a one-standard deviation increase in the lagged 12-month return of the S&P 500 index (12.5 percentage point) is associated with a 3.7 percentage point decline in demand for HIGH. On the other hand, we find (weak) evidence that demand for financial advisors is higher when the standard deviation of the monthly returns of the S&P 500 index over the prior 12 months is lower. One interpretation is that differences in returns are more salient than differences in volatility. However, we cannot rule out the possibility that volatility simultaneously impacts the choice between ORP and PERS.[12]

In summary, our evidence on which participants choose HIGH versus LOW is largely consistent with the existing literature on financial literacy. Older, more highly educated, and more highly paid employees are more likely to be financially literate and less likely to value personalized service from financial advisors. In the next section, we use account-level data from HIGH and LOW to compare the risk-adjusted, after-fee returns of these two groups of investors.

III. Asset Allocation and Performance Differences Between HIGH and LOW

A. What Differences Do We Expect to Observe?

Before comparing the portfolios of HIGH and LOW investors, it is important to consider how and why these portfolios may differ. If variation in demand for financial advisors is driven primarily by variation in financial literacy, there are two cases to consider. On the one hand, financial advisors may help guide HIGH investors to age-appropriate asset allocation plans. In this case, we expect HIGH investor asset allocation decisions to be "at least as good" as self-directed LOW investor behavior. For example, HIGH portfolios may include significantly larger allocations to foreign equity (i.e., exhibit less home bias), be less likely to remain fully invested in the default investment option, less likely to naively chase past investment returns, and less likely to adjust their asset allocations in response to the recent financial crisis. If financial services and financial literacy are perfect substitutes, HIGH and LOW investors should both exhibit optimal behavior, with differences in performance due entirely to the higher fees that HIGH in-

[12] Because we lack data on those OUS employees who do not choose ORP, we cannot study the impact of recent equity market returns on the choice between defined contribution and defined benefit retirement plans. Brown and Weisbenner (2007) study the choice between DC and DB retirement plans in the State Retirement System of Illinois. Their finding that participants with greater levels of financial sophistication are more likely to choose the DC is similar in spirit to our finding that participants with greater levels of financial literacy are more likely to choose LOW over HIGH.

vestments charge to compensate HIGH financial advisors. Furthermore, if the guidance that HIGH investors receive lead to fewer mistakes, they may recover some of the fees paid to the financial advisors in the form of higher (less volatile) returns.

On the other hand, there may be agency conflicts between financial advisors and their clients. For example, just as Reuter and Zitzewitz (2006) find that the financial media encourages return chasing and churning by publishing monthly articles that tout recent winners, financial advisors may encourage their clients to invest in actively managed funds with high past returns. Or, as Carlin (2009) argues, financial advisors may exploit their clients' lower levels of financial literacy by recommending riskier investments—a strategy that makes it easier to mask underperformance. Of course, interpreting differences in risk taking as evidence of agency conflicts, requires the further assumption that HIGH and LOW investors have similar risk preferences (controlling for observable demographic characteristics).

As noted above, comparisons between HIGH and LOW are complicated by the fact that HIGH bundles access to personalized face-to-face service with access to significantly more investment options. This raises the possibility that ORP participants who do not value financial guidance will nevertheless choose HIGH so that they can invest in, for example, the HIGH International Equity Fund. One argument against this possibility is that, in Section II.D, we find evidence that demand for HIGH falls as the investment menu grows in size. A second argument is that every ORP participant who invests through HIGH is paying for personalized service in the form of higher fees—even those who do not interact with their financial advisor. In other words, for those who do not value the services of financial advisors, access to the HIGH investment menu comes at a significant cost.

B. Overview of Account-Level Data from HIGH and LOW

In the analysis below, we combine the participant-level data from OUS with two types of participant-level data from HIGH and LOW. First, we observe how each participant's monthly ORP contribution is allocated across the available investment vehicles. The monthly contribution data from HIGH begin in October 1996, when ORP is introduced, and ends in December 2009. However, the monthly contribution data from LOW does not begin until December 1997. Since we infer enrollment dates from the date of the first monthly retirement contribution, enrollment dates for ORP participants investing through LOW are left censored at December 1997. Therefore, we limit any test that depends on date on the choice, such as tests for return chasing in the initial choice of investments, to the period January 1998 through December 2009.

Second, we observe how much each participant has invested in each investment vehicle. The account balance data from HIGH is monthly; it begins in October 1996 and ends in December 2009. However, the account balance data from LOW is annual; it begins in December 1998 and ends in December 2009. The lack of monthly account balance data from LOW limits several of our tests. Most significantly, it forces us to focus on differences in annual after-fee returns.[13]

C. Comparing After-Fee Returns Earned by HIGH and LOW Investors

We begin by comparing the annual after-fee returns earned by ORP participants choosing LOW versus HIGH. To calculate the annual after-fee return of participant *i* in year *t*, we combine data on participant i's ORP account balances at the end of years *t* and *t-1* with data on the contributions that participant i made to ORP during year t . Our sample of annual returns begins with 1999 (because account balance data from LOW begin in December 1998) and ends with 2009. During this eleven-year period, the average annual after-fee return earned by an ORP participant is 1.61 percent. Over the same period, the average annual return on the S&P 500 index

[13] While HIGH and LOW provided us with data on historical (after-fee) monthly returns, they did not provide us with data on annual expenses. Because the majority of these investments are variable annuities, fee data are not available from standard mutual fund databases such as CRSP and Morningstar.

is 3.02 percent. The lower average return earned by ORP participants reflects the lower levels of systematic risk, and the impact of the fees paid to HIGH and LOW.

The more interesting comparison is between the after-fee returns earned by participants investing through HIGH and LOW. Because HIGH must compensate its financial advisors for providing one-on-one service, when we hold investment choice and investment behavior constant, we expect HIGH investors to earn lower annual returns than LOW investors. Indeed, in Table 4, we find that the average annual after-fee returns earned by HIGH investors are approximately one percentage point lower than those earned by LOW investors (0.89 percent versus 2.08 percent). By way of comparison, sales commissions on broker-sold mutual funds typically equal one percent of assets under management.

The average difference of 1.19 percent masks significant time-series variation in relative performance. For example, HIGH underperforms LOW by 8.73 percent in 2000 and outperforms LOW by 8.85 percent in 2009. In general, HIGH investors earn higher after-fee returns when U.S. equity markets post strong positive returns (1999, 2003, 2009) and lower after-fee returns when they post strong negative returns (2000-2002, 2008). Consistent with these patterns, we see the typical HIGH investor has greater exposure to systematic risk than LOW (as measured by an average Beta of 0.77 versus 0.59).[14] We also see that the standard deviation of annual returns is higher within the sample of HIGH investors than in the sample of LOW investors (25.15% versus 20.56%). To the extent that HIGH and LOW investors differ primarily with respect to their financial literacy, these broad differences in portfolio risk could reflect too little risk taking by LOW investors or too much risk taking by HIGH investors.

[14] To obtain estimates of Beta, SMB, HML, and MOM for investment j in December t-1, we estimate Carhart's (1997) four-factor model using monthly returns over the prior 24 months. To obtain the asset-weighted Beta for participant i's portfolio in calendar year t, we weight the beta of each investment by the fraction of participant's i portfolio allocated to investment j in December t-1.

In Table 5, we turn to multivariate regressions of the returns earned by HIGH and LOW investors. We begin by regressing the average annual after-fee return earned by ORP participant i in year t on a dummy variable indicating whether participant i invests through HIGH in year t, as well as a separate dummy variable for each calendar year. By comparing HIGH returns to LOW returns within the same year, columns (1) controls for time-series variation in aggregate market returns. However, this specification does not control for the fact that HIGH and LOW investor portfolios have different average exposures to risk. Therefore, in column (2), we add two sets of portfolio-level controls. We control for the fraction of participant i's portfolio that is allocated to fixed annuities, money markets, bonds, balanced funds, domestic equity, foreign equity, and real estate in December t-1. We also control for the weighted-average factor loadings (Beta, HML, SMB, MOM) of participant i's portfolio in December t-1. In column (3), we allow the impact of asset allocation and factor loadings on returns to vary across years by interacting each asset allocation and factor loading variable with the full set of calendar year dummy variables. Finally, in column (4), we include a full set of participant-level controls interacted with the full set of calendar year dummy variables. Standard errors in columns (1) through (4) are clustered on both calendar year and participant. (Clustering on year allows return shocks to be correlated across all participants in the same year, but effectively reduces the number of observations from twenty thousand participant years to eleven years.) In columns (5) and (6), we re-estimate two of the OLS specifications using Fama-MacBeth.

When we ignore within-year differences in portfolio composition and risk, in column (1), the estimated coefficients on the HIGH dummy variable is -0.83 percent. This difference is similar in magnitude to the difference in Table 4, but statistically indistinguishable from zero. In contrast, when we control for lagged asset allocations and factor loadings, in columns (2) through (6), the estimated coefficients range from -2.24 to -2.62 percent and are all statistically significant from zero at the 5-percent level (and below). Despite being limited to eleven years of annual returns, we find strong evidence that HIGH investors underperform LOW investors on a risk-adjusted basis.

One potential explanation for the underperformance of HIGH investors is that the investments available through HIGH significantly underperform those available through LOW. For example, Bergstresser, Chalmers, and Tufano (2009) find that mutual funds targeted at broker-advised investors underperform mutual funds targeted at do-it-yourself investors by approximately one percent per year after adding back the (12b-1) fees paid to brokers. Focusing on after-fee returns, we find much smaller return differences. Specifically, in column (7), when we switch our focus to the annual after-fee returns earned by investment *j* in calendar year *t*, we find that investments available through HIGH underperform by approximately 0.57 percent per year. In other words, if HIGH investors picked investments at random, we would have expected HIGH investors to underperform by a smaller margin. Next, we explore differences in asset allocation and investment selection, with the goal of identifying margins along which financial advisors plausibly impact investor behavior.

D. Comparing the Asset Allocation Decisions of HIGH and LOW Investors

In this section, we compare the asset allocation decisions of HIGH and LOW investors. We begin by comparing the number of investment options in which the different investors choose to invest. The unit of observation is participant i, twelve months after the initial ORP contribution. In Panel A of Table 6, we find that HIGH investors allocate their retirement contributions across more investments than LOW investors. The mean difference is 2.14 (5.76 versus 3.62), which is statistically different from zero at the 1-percent level. The larger number of investments in the typical HIGH portfolio raises the possibility that financial advisors help HIGH investors construct more diversified portfolios. However, we have already seen that the standard deviation of monthly returns is higher for HIGH investors than for LOW investors. Alternatively, because HIGH's investment menu is significantly larger than LOW's investment menu, the patterns in Panel A are consistent with larger investment menus leading investors (and financial advisors) to allocate retirement contributions across more investments for reasons unrelated to optimal asset allocation.[15]

In Panel B, we focus on aggregate retirement contributions to seven asset classes: annuities, money market funds, bonds, balanced funds, domestic equity, foreign assets (primarily equity), and real estate. Comparing the average fraction of participant i's retirement contribution allocated to each asset class, we see that HIGH investors have significantly higher allocations to domestic equity (60.0% versus 41.2%, even ignoring the small allocation to balanced funds), and significantly lower allocations to fixed annuities, money markets, and bonds.[16] These differences help to explain the different levels of systematic risk that we documented in Table 4. At the same time, the allocation to foreign assets is similar (16.8% versus 15.8%), suggesting similar levels of home bias in the two sets of portfolios.

Because these differences control for neither the different dates on which the initial asset allocation decisions are made, nor the different demographics characteristics of HIGH and LOW

[15] Benartzi and Thaler (2001) document a positive correlation between the number of funds offered in a retirement account and the number of funds in which participants invest. While our findings are inconsistent with the "1/N" allocation rule that they find investors use within their retirement accounts, the investment menus offered by HIGH and LOW are significantly larger than those of most of the plans in their study.

[16] Because balanced funds invest in both debt and equity, allocations to balanced funds should be apportioned to debt and equity. Similarly, because global funds invest in both domestic and international assets, allocations to global funds should be apportioned to debt, domestic equity and foreign. For the balanced and globabl equity funds offered by LOW, we possess the underlying allocation data required to apportion fund-level assets across bonds, domestic equity, and foreign equity. However, we lack the underlying asset allocation data for balanced and global funds available through HIGH.

investors, we estimate the following OLS regression:

$$allocation_{it} = \alpha + \lambda HIGH_{it} + \beta X_{it} + \eta_t + \varepsilon_{it} \tag{1}$$

where $allocation_{it}$ is a measure of participant i's asset allocation in month t, $HIGH_{it}$ is a dummy variable that indicates whether participant i invests through HIGH, X_{it} is the full set of participant-level controls from Table 3, and we include a separate fixed effect for month t, to control for the possibility of unobserved trends in optimal asset allocation. Standard errors are clustered on month t. We find that all of the differences—except for the allocation to foreign assets—are statistically different from zero at the 1-percent level. Including participant controls has little impact on economic or statistical significance.

There are three other differences worth noting. First, HIGH investors have significantly higher allocations to index funds (19.7% versus 8.1%). While index funds tend to offer higher expected returns than actively managed funds because of their lower fees (Gruber (1996)), HIGH index funds eliminate much of this benefit by charging the higher fees required to compensate their financial advisors (Elton, Gruber, and Busse (2004)). Furthermore, HIGH index funds like the HIGH Nasdaq 100 Index Fund are more narrowly focused than the LOW Equity Index Fund, offering less diversification.

Second, HIGH investors only allocate 58.2% of their retirement contributions to investments advised by HIGH. The other 41.8% of their contributions are allocated to investments managed by other asset management firms (such as the SIT Mid-Cap Growth Fund). One explanation for this pattern is that, because HIGH financial advisors receive compensation from all of the investment options available through HIGH's investment menu, they are able to guide investors toward the best choice within each asset class.

Finally, Madrian and Shea (2000) find that a substantial fraction of retirement plan participants "choose" to invest in the default investment option. Therefore, financial advisors can potentially benefit participants by guiding them to more suitable investment options. In our sample, this appears to be the case. While 9.2% of LOW investors contribute 100% of their retirement contributions to the default (money market), only 2.0% of HIGH investors contribute 100% of their retirement contributions to the default (fixed annuity). In unreported probit regressions that include time-period fixed effects and participant controls, we find that the difference increases from 7.2 to 7.6 percentage points and is statistically different from zero at the 1-percent level. Given our evidence that HIGH investors have lower levels of financial literacy, this difference is likely to reflect the causal impact of financial advisors on asset allocation.

D. Comparing the Factor Loadings of HIGH and LOW Investors' Portfolios

Because our asset class-level comparisons are complicated by the different investment options available through the two providers, in Table 7, we switch our focus from asset allocations to factor loadings. The unit of observation is again participant i, twelve months after the initial ORP contribution. For investment j in month t, we estimate Carhart (1997)'s four-factor model using the prior 24 monthly returns. Next, we use lagged monthly asset allocation data to convert investment-level factor loadings on the market (Beta), small minus big mimicking portfolio (SMB), high minus low mimicking portfolio (HML), and momentum portfolio (MOM) into asset-weighted portfolio-level factor loadings.[17] Finally, we regress portfolio-level factor loading for participant i in month t on the same set of control variables as in equation (1) and report the estimated coefficients on the HIGH dummy variable. We find that HIGH portfolios have larger loadings on beta, size, book-to-market, and momentum than LOW portfolios, implying

[17] While we would prefer to construct asset-weighted averages using lagged account balance data rather than lagged contribution data, we only possess account balance data for LOW at year's end. However, the correlation between fraction of participant i's portfolio allocated to asset class k and the fraction of participant i's retirement contributions allocated to asset class k ranges from 0.8688 to 0.9504.

that HIGH investors hold riskier investments than LOW investors. One possibility is that HIGH financial advisors intentionally guide their clients toward riskier investments. Another possibility is that the HIGH investment menu is skewed toward riskier investments.

In the remaining columns of Table 5, we compare the factor loadings of the two investment menus. The unit of observation is investment j in month t, and the sample is limited to those investment-month pairs during which the investment is available to ORP participants. We find that HIGH investments have significantly higher loadings on the market, size, and momentum than LOW investments. However, the estimated coefficients on the market, size, and book-to-market are significantly lower in the benchmark regressions, suggesting that the higher factor loadings in the portfolio-level regressions are due to more than chance. Given our evidence that demand for HIGH is higher among those with lower financial literacy, we find it more likely that financial advisors steer HIGH investors toward specific types of investments than that HIGH investors inherently prefer these types of investments.

E. Comparing the Return-Chasing Behavior of HIGH and LOW Investors

To implement an asset allocation plan, an investor must allocate her monthly retirement contributions across the appropriate set of funds. Within the full universe of mutual funds, there is strong evidence that the relation between inflows and performance is convex, with the best performing mutual funds receiving a disproportionate share of the dollars.[18] At the same time, because studies like Carhart (1997) find little evidence that abnormal performance is persistent, investors should not allow recent returns to distort their asset allocation decisions. In Table 6, we explore the impact of financial advisors on investment selection by testing whether return-chasing behavior is stronger among self-directed investors.

[18] See, for example, Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998), and Del Guercio and Tkac (2002).

Our dependent variable is the fraction of participant i's retirement contribution that is allocated to investment j in month t. The sample consists of all ORP participants for whom the enrollment date is uncensored, and all funds available to HIGH or LOW investors in month t. The independent variables of interest are the net return on fund j over the prior twelve months interacted with dummy variables that indicate whether participant i invests through HIGH or LOW. We control for the funds broad asset category and lagged factor loadings, and for the full set of participant-level controls from Table 3. Because we are testing for a differential sensitivity to lagged returns across ORP providers, we also include a separate fixed effect for each provider each month, so that we are comparing fund returns within each menu relative to the other funds within the same menu. Because we lack data on the level of fund expenses, we are unable to assess the impact of fees on fund selection. Standard errors are clustered on date (but inference is unchanged when we cluster on both date and participant).

In the first column, we focus on asset allocations in the first month that we observe an ORP retirement contribution. The coefficient estimates on both interaction terms are positive and statistically different from zero, suggesting that both HIGH and LOW investors take recent returns into consideration when selecting funds. While the incremental R^2 associated with the return measures is modest (0.0037 out of 0.0804), we cannot reject the hypothesis that the two coefficients are equal (p-value of 0.3959). In other words, investors with access to guidance from financial advisors exhibit the same degree of return chasing behavior in month 1 as self-directed investors.

When we switch our focus from month 1 to month 24, we find little evidence of return chasing behavior. Therefore, while LOW investors and HIGH investors both appear to respond to recent returns when choosing funds, neither set of investors adjusts their fund-level allocations in response to subsequent returns. This suggests a similar degree of inertia on the parts of self-directed and financial advisor-guided investors. Inferences are similar when we focus on a narrower set of asset classes. They are also similar when, in unreported specifications, we include interactions with both lagged return and lagged return squared.

F. Are HIGH Investors Less Likely to Change Their Allocation to Domestic Equity During the Financial Crisis?

In addition to helping an investor decide on an asset allocation plant, a financial advisor may also help the advisor adhere to this plan when market conditions change. For example, investors who invest through financial advisors may have been less likely to liquidate their equity holdings during the steep market decline of 2008-2009. In this section, we study the frequency with which ORP participants adjust their allocation to domestic equity, exploiting the fact that our asset allocation data extend through December 2009.[19] Rather than compare the behavior of HIGH and LOW investors in 2008-2009, we take a difference-in-difference approach. For a given investment horizon and time period, we determine the fraction of ORP participants that increased, decreased, or made no change to the fraction of their retirement contribution allocated to domestic equity funds. We then compare changes in the behavior of HIGH investors between 1997-2007 and 2008-2009 to changes in the behavior of LOW investors between 1997-2007 and 2008-2009.

In Table 7, we analyze investment horizons of 3 months (Panel A) to 12 months (Panel B). As expected, the likelihood that an ORP participant increases or decreases the allocation to domestic equity increases with the length of the investment horizon. Since our findings are

[19] Because we only possess annual data from LOW on investor account balances, our analysis in this section focuses on monthly data from LOW and HIGH on how retirement contributions are allocated across broad asset classes. In the next draft, we will incorporate the annual data on investor account balances into the analysis.

qualitatively similar across both horizons, we focus our discussion on Panel B. During the 1999-2007 period, HIGH and LOW investor behavior is similar. Approximately 80 percent of ORP participants make no change in their allocation to domestic equity, which is consistent with the investor inertia documented in Agnew, Balduzzi, and Sunden (2003). Of the remaining 20 percent of investors, half increase their allocation to domestic equity, and half decrease it. During the 2008-2009 period, HIGH investors are more likely to stick with their existing allocation to domestic equity than LOW investors (86.6 percent versus 80.7 percent), which is consistent with financial advisors helping investors adhere to their initial asset allocation plan. However, conditional on changing their allocation to domestic equity during the 2008-2009 period, HIGH investors are more likely to decrease their allocation than to increase it.

To test for changes in the frequency of each type of adjustment, we estimate the following pooled OLS regression:

$$adjust_{it} = \alpha + \delta\left(HIGH_{it} \times Crisis_{it}\right) + \lambda HIGH_{it} + \beta X_{it} + \eta_t + \varepsilon_{it} \qquad (2)$$

where $adjust_{it}$ is one of three dummy variables that indicate whether participant i increased, decreased, or made no change to her allocation to domestic equity in period t, $HIGH_{it}$ is a dummy variable that indicates whether participant i invested through HIGH at the beginning and end of period t, X_{it} is the full set of participant-level controls from Table 3, and we include a separate fixed effect for each period t. The difference between regressions "With Controls" and "Without Controls" is the inclusion or exclusion of X_{it}. Standard errors are clustered on time period.

Our difference-in-difference estimates confirm that HIGH investors were differentially less likely to adjust their allocation to domestic equity during the recent financial crisis. The change is economically significant, ranging from 2.64 percentage points in Panel A to 9.98 percentage points in Panel B. The fact that significantly fewer HIGH investors change their equity allocation in 2008-2009 may reflect a decreased likelihood to increase equity allocations during this period, a decreased likelihood to decrease equity allocations during this period, or both. (By construction, the three difference-in-difference estimates sum to zero.)

In general, we find a greater reduction in the likelihood to increase allocations to domestic equity. For example, when we focus on the 12-month investment horizon, the estimated coefficient ranges from -6.59 percentage points (without participant-level controls) to -6.98 percentage points (with participant-level controls), and both coefficients are significantly different from zero at the 5-percent level. In other words, while participants investing through HIGH were differentially less likely to adjust their asset allocations during the financial crisis (broadly defined), financial advisors appear to have been relatively more successful in preventing HIGH investors from increasing their allocation to domestic equity than in preventing them from decreasing their allocation to domestic equity. In the future, we hope to shed more light on the link between the lagged return earned by participant i's portfolio and changes in asset allocation.

IV. Conclusion

In this paper, we study the impact of financial advisors on retirement savings behavior. Combining unique investor-level data from the Oregon University System with account-level data from HIGH and LOW, we attempt to answer two important questions. First, who chooses to receive personal face-to-face financial service by investing through HIGH? Second, are there discernable differences in the investment outcomes of HIGH and LOW investors?

With respect to the choice of provider, we find that demand for personalized financial service responds to standard proxies for the level of a participant's financial literacy. In particular, we find that younger, less highly educated, and less highly paid employees are more likely to choose HIGH. The fact that investors with lower levels of financial literacy are more likely to invest through financial advisors leads us to ask whether financial advisors are effective substitutes for financial literacy. To the extent that HIGH investors receive sensible advice on asset allocation and investment decisions, they should underperform self-directed investors by no more than the fees paid to the financial advisors.

Between 1999 and 2009, the average HIGH investor earns an annual after-fee return of 0.89 percent, while the average LOW investor earns an annual after-fee return of 2.08 percent. This difference in annual returns is consistent with the fact that fees for financial advice in other settings average one percent of assets per year. However, the one percentage point difference masks the fact that the standard deviation of HIGH returns is significantly higher (25.1% versus 20.5%). When we switch our focus from raw to risk-adjusted after-fee returns, we find that HIGH investors underperform LOW investors by between 224 and 263 basis points per year. The fact that underperformance increases when we control for portfolio risk is consistent with the theoretical argument in Carlin (2009) that economic rents are more easily extracted when uncertainty is higher. However, it is also consistent with differences in investor preferences.

When we analyze the portfolios of HIGH and LOW investors, several interesting patterns emerge. HIGH investors purchase more funds than LOW investors, and they allocate a larger fraction of their retirement contributions to index funds. They are also less likely to invest solely in the default investment options for new participants, and less likely to change their allocation to domestic equity during the financial crisis. Collectively, these differences suggest that financial advisors help HIGH investors pursue stable, diversified investment strategies. On the other hand, we find that HIGH portfolios display significantly greater exposure to systematic market risk, small firms, high market to book firms and firms with a larger momentum factor. While these factors are associated with higher average returns, they are also associated with greater risk taking by HIGH investors.

Despite the significant return differences, we cannot conclude that HIGH financial advisors fail to provide valuable services to their clients. For example, the fact that HIGH investors are less likely to remain fully invested in the default investment option strongly suggests that financial advisors provide guidance on asset allocation. Moreover, investors with lower levels of financial literacy may derive significant value from being able to meet one-on-one with an advisor, especially when the market has been unusually volatile (Bergstresser, Chalmers, and Tufano (2009)). However, the fact that self-directed investors outperform financial advisor-guided investors by more than two percent per year provides a new estimate of the value of financial literacy. For the average HIGH investor losing two percent per year corresponds to an annual "tax" of $688. In this sense, we can conclude that financial advisors are an imperfect substitute for financial literacy. Of course, if financial literacy cannot be effectively taught at lower cost, allowing those with less financial literacy to invest through financial advisors will be second best.

Finally, while our findings are highly suggestive of how financial advisors may impact the retirement savings decisions of ORP participants, we cannot use them to quantify the overall causal impact of financial advisors on retirement savings. Specifically, our findings do not tell us how HIGH investors would have invested in the absence of access to financial advisors (or how LOW investors would have invested if they had been forced to invest through HIGH). In future work, we hope to exploit the fact that OUS eliminated access by new ORP participants to HIGH in November 2007, when it changed the ORP provider menu. Unfortunately, the fact that existing HIGH investors were allowed to continue investing through HIGH significantly reduces the sample of constrained investors, limiting the power of these comparisons.

Appendix. Overview of the HIGH and LOW Investment Menus

ORP participants face different investment menus when they invest through HIGH and LOW. In Table A1, we report the number of investment options in each asset class at the beginning and end of our sample period. We also report the number of investment options that are actively versus passively managed, and the number of investment options that advised by the provider versus outside asset management firms (for example, HIGH provides access to the HIGH Small-Cap Value Fund, which is advised by HIGH, and the SIT Mid-Cap Growth Fund, which is advised by SIT). There are several notable differences between the two investment menus. First, HIGH offers four-times as many investment options as LOW in October 1996 (40 versus 10). Even after LOW increases its investment menu in July 2007, HIGH still offers more than three-times as many investment options (61 versus 19). Second, HIGH's investment menu is skewed toward domestic equity, offering investments with narrow investment mandates (such as Small-Cap Value or Mid-Cap Growth). Third, HIGH does not offer any exposure to real estate. Fourth, while HIGH's investment menu grows significantly over our sample period, access to investments advised by other firms declines significantly. For example, HIGH introduces its own Mid-Cap Growth Fund in September 1998 and drops the SIT Mid-Cap Growth Fund in May 2006. Finally, between October 1996 and October 2007, when ORP participants are allowed to choose between HIGH and LOW, the two providers have different default investments. The default in LOW is a money market, while the default in HIGH is a fixed annuity.

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Table 1. Number of New ORP Participants by Provider, January 1999 - October 2007

Date Range	**LOW**	**HIGH**	SMALL	SMALLER	TOTAL
01/99 and before	**699**	**603**	274	66	1,642
02/99 - 12/99	**169**	**141**	55	24	389
01/00 - 12/00	**192**	**153**	57	25	427
01/01 - 12/01	**204**	**108**	52	15	379
01/02 - 12/02	**229**	**91**	56	14	390
01/03 - 12/03	**275**	**133**	28	31	467
01/04 - 12/04	**244**	**130**	45	18	437
01/05 - 12/05	**294**	**197**	46	37	574
01/06 - 12/06	**285**	**148**	53	30	516
01/07 - 10/07	**355**	**139**	57	35	586
TOTAL	**2,946**	**1,843**	723	295	5,807
	(50.7%)	***(31.7%)***	*(12.5%)*	*(5.1%)*	

Note: We use Oregon University System payroll data to identify the provider to which new ORP participants direct their retirement contributions. The unit of observation is participant i in the first month that she contributes to her ORP (401(a)) account. During our sample period, participants have the choice of four providers, which we refer to as LOW, HIGH, SMALL, and SMALLER. Our focus is on HIGH, which markets itself as providing personal face-to-face service, and LOW, which does not. Because OUS payroll data begin in January 1999, initial contribution dates before February 1999 are left censored at January 1999. Because new ORP participants are not allowed to choose HIGH as their ORP provider after October 2007, our sample of new ORP participants ends in October 2007.

Table 2. Summary Statistics for New ORP Participants, by Provider, January 1999 - October 2007

	Percentages in columns sum to 100%					Percentages in rows sum to 100%			
	Full Sample (1)	**LOW** (2)	**HIGH** (3)	SMALL (4)	SMALLER (5)	**LOW** (6)	**HIGH** (7)	SMALL (8)	SMALLER (9)
Sample Size	5,807	**2,946**	**1,843**	723	295	**50.7%**	**31.7%**	12.5%	5.1%
Monthly Salary (mean)	$4,399	**$4,796**	**$3,892**	$4,226	$3,996	**$4,796**	**$3,892**	$4,226	$3,996
Monthly Salary (median)	$3,823	**$4,097**	**$3,460**	$3,700	$3,351	**$4,097**	**$3,460**	$3,700	$3,351
Female	45.6%	**42.4%**	**48.0%**	50.6%	50.2%	**47.1%**	**33.4%**	13.8%	5.6%
Age < 30	16.2%	**12.3%**	**20.1%**	20.2%	21.7%	**38.5%**	**39.2%**	15.5%	6.8%
30 >= Age < 40	37.6%	**39.7%**	**35.4%**	34.4%	39.0%	**53.5%**	**29.9%**	11.4%	5.3%
40 <= Age < 50	27.0%	**27.8%**	**26.2%**	27.9%	22.4%	**52.2%**	**30.8%**	12.9%	4.2%
50 >= Age	19.1%	**20.2%**	**18.3%**	17.4%	16.9%	**53.7%**	**30.4%**	11.4%	4.5%
PhD	33.2%	**38.1%**	**27.5%**	31.4%	24.4%	**58.2%**	**26.3%**	11.8%	3.7%
Masters	19.5%	**17.1%**	**22.4%**	20.7%	21.7%	**44.7%**	**36.4%**	13.3%	5.7%
Bachelors	14.4%	**9.3%**	**19.8%**	18.9%	20.7%	**32.9%**	**43.5%**	16.4%	7.3%
undisclosed (32.9%)	32.9%	**35.5%**	**30.4%**	28.9%	33.2%	**54.6%**	**29.3%**	10.9%	5.1%
Asian	6.9%	**6.9%**	**6.6%**	8.3%	4.7%	**51.0%**	**30.5%**	15.0%	3.5%
Black	2.2%	**2.2%**	**2.7%**	1.4%	1.7%	**50.4%**	**38.0%**	7.8%	3.9%
Hispanic	2.9%	**3.1%**	**3.0%**	1.9%	2.0%	**54.2%**	**33.7%**	8.4%	3.6%
White	74.9%	**73.1%**	**76.6%**	76.6%	78.3%	**49.5%**	**32.5%**	12.7%	5.3%
Other	1.6%	**1.4%**	**2.2%**	1.0%	1.4%	**45.2%**	**43.0%**	7.5%	4.3%
undisclosed (11.5%)	11.5%	**13.3%**	**8.9%**	10.8%	11.9%	**58.6%**	**24.5%**	11.7%	5.2%
Oregon State University	32.1%	**34.3%**	**22.4%**	42.0%	46.1%	**54.3%**	**22.1%**	16.3%	7.3%
University of Oregon	28.4%	**26.9%**	**31.9%**	26.3%	26.1%	**48.1%**	**35.7%**	11.5%	4.7%
Portland State University	20.5%	**20.3%**	**24.0%**	16.0%	11.9%	**50.2%**	**37.1%**	9.7%	2.9%
Oregon Institute of Technology	5.0%	**3.9%**	**7.1%**	3.9%	5.4%	**39.4%**	**45.3%**	9.7%	5.5%
Western Oregon University	5.0%	**4.8%**	**5.8%**	4.7%	4.1%	**48.1%**	**36.2%**	11.6%	4.1%
Southern Oregon University	4.2%	**4.8%**	**3.7%**	3.0%	3.7%	**58.4%**	**28.0%**	9.1%	4.5%
Eastern Oregon University	3.6%	**3.6%**	**4.4%**	2.1%	1.7%	**50.7%**	**39.6%**	7.2%	2.4%
Office of the Chancellor	1.2%	**1.4%**	**0.7%**	1.9%	1.0%	**57.7%**	**18.3%**	19.7%	4.2%

Note: In this table, we provide summary statistics for the sample of ORP participants described in Table 1. We lack educational data for 33.5% and ethnicity data for 11.6% of the ORP participants. Age is calculated in the month that we observe the first contribution to the provider, which is left censored at January 1999 for 28.3% of the participants.

Table 3. Predicting Demand for a Financial Advisor, January 1999 - October 2007

Dependent:	= 1 if ORP participant i makes initial ORP contribution to provider HIGH			
Sample:	ORP Participants who choose either HIGH or LOW			
	(1)	(2)	(3)	(4)
Salary	-0.0358 ***	-0.0265 ***	-0.0258 ***	-0.0270 ***
	(0.0033)	(0.0044)	(0.0066)	(0.0066)
Female	0.0026	-0.0248	-0.0325	-0.0338
	(0.0130)	(0.0179)	(0.0273)	(0.0276)
Age [30, 40)	-0.1048 ***	-0.0681 ***	-0.0792 **	-0.0783 **
	(0.0207)	(0.0261)	(0.0319)	(0.0316)
Age [40, 50)	-0.0699 **	-0.0229	-0.0787 **	-0.0815 **
	(0.0264)	(0.0369)	(0.0374)	(0.0363)
Age [50, 100]	-0.0442	0.0318	-0.0755 *	-0.0671
	(0.0459)	(0.0509)	(0.0445)	(0.0450)
Asian		0.0548	0.1097 ***	0.1133 ***
		(0.0429)	(0.0388)	(0.0399)
Black		0.0055	0.0590	0.0691
		(0.0679)	(0.0830)	(0.0832)
Hispanic		0.0011	0.0264	0.0358
		(0.0457)	(0.0578)	(0.0581)
Other		0.0028	0.0273	0.0242
		(0.0723)	(0.0847)	(0.0842)
PhD		-0.1903 ***	-0.1993 ***	-0.2108 ***
		(0.0293)	(0.0299)	(0.0311)
Masters		-0.1114 ***	-0.1030 ***	-0.1121 ***
		(0.0227)	(0.0297)	(0.0297)
Ratio of # options in HIGH			-0.0995 **	0.0069
to # options in LOW			(0.0435)	(0.0480)
Return of S&P 500 index			-0.2136 *	-0.2921 *
over prior 12 months			(0.1163)	(0.1531)
Volatility of S&P 500 index			-1.0237 **	-0.9389
over prior 12 months			(0.4748)	(1.3147)
OSU	-0.1350 ***	-0.1523 ***	-0.1978 ***	-0.2011 ***
	(0.0280)	(0.0330)	(0.0318)	(0.0331)
PSU	0.0000	-0.0227	-0.0211	-0.0187
	(0.0194)	(0.0227)	(0.0345)	(0.0326)
OIT	0.0830	0.0524	-0.0944	-0.1047 *
	(0.1107)	(0.1100)	(0.0606)	(0.0582)
WOU	-0.0277			
	(0.0767)			
SOU	-0.1316 **			
	(0.0482)			
EOU	-0.0370			
	(0.0704)			
Chancellor	-0.1518			
	(0.1031)			

Sample begins in Feb 1999?	---	---	Yes	Yes
Year FEs?	---	---	---	Yes
N	4,503	2,581	1,700	1,700
Pseudo-R2	0.0434	0.0579	0.0784	0.0902

Note: In this table, we report marginal effects estimated via probit. The unit of observation is participant i in the first month we observe a retirement contribution payment to an ORP provider. The sample ends in October 2007, and is restrict to the 82.5% of ORP participants who choose either the HIGH or LOW provider. The dependent variable equals one if participant i chooses HIGH. In column (1), we focus on the full sample of ORP participants for which we observe salary, gender, age, and employer (the omitted category is the University of Oregon). Columns (2)-(4) include variables related to ethnicity and educational attainment. Omitted categories are "White" and "Bachelors Degree". Column (4) includes calendar year fixed effects. In column (2), we restrict the sample to participants (and campuses) with educational attainment data. The sample shrinks further in columns (3)-(4), when we exclude participants for whom the initial retirement contribution date is left censored at January 1999. However, by focusing on participants for whom the ORP enrollment data is February 1999 and later, we are able to include controls for the return and volatility of the S&P 500 over the prior 12 months, and for the ratio of the number of investment options in HIGH to the number of investment options in LOW. Standard errors are clustered on the date that we observe the first retirement contribution. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 4. Annual After-Fee Returns and Betas, HIGH versus LOW, 1999-2009

	Average Annual After-Fee Return		Standard Deviation of Annual After-Fee Return		Average Beta	
	LOW	HIGH	LOW	HIGH	LOW	HIGH
	(1)	(2)	(3)	(4)	(5)	(6)
1999	23.10%	29.28%	12.16%	23.60%	0.69	0.74
2000	-11.90%	-20.63%	14.09%	17.34%	0.69	0.78
2001	-10.82%	-18.36%	9.29%	19.20%	0.66	0.86
2002	-17.73%	-18.73%	16.57%	11.62%	0.65	0.94
2003	20.14%	25.40%	17.82%	13.32%	0.59	0.85
2004	9.11%	8.92%	13.71%	14.85%	0.60	0.77
2005	6.09%	5.43%	9.15%	9.25%	0.59	0.77
2006	11.42%	11.35%	8.93%	7.84%	0.58	0.74
2007	1.32%	-2.68%	21.72%	22.14%	0.58	0.72
2008	-23.43%	-31.17%	14.50%	15.19%	0.54	0.70
2009	15.48%	24.33%	12.73%	16.68%	0.51	0.75
1999-2009	2.08%	0.89%	20.56%	25.12%	0.59	0.77

Note: The unit of observation is ORP participant i in calendar year t. The sample consists of all HIGH and LOW participants for which we observe retirement account contribution data in calendar year t and account balance data in both December t and December t-1. Beta is the asset-weighted beta of participant i's portfolio in December t-1. The betas of the underlying investments are estimated by running the Carhart (1997) four-factor model on investment-level returns over the 24 months prior to the start of each calendar year.

Table 5. Testing for Differences in Annual After-Fee Returns, HIGH versus LOW, 1999-2009

Dependent:	*After-fee Return Earned by ORP Participant i in Calendar Year t*						*After-fee Return of Investment j in Calendar Year t*
Estimation:	OLS	OLS	OLS	OLS	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HIGH	-0.0083	-0.0243 **	-0.0262 ***	-0.0244 ***	-0.0252 **	-0.0224 **	-0.0058 **
	(0.0181)	(0.0111)	(0.0096)	(0.0092)	(0.0090)	(0.0084)	(0.0025)
Year FEs?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged factor loading controls?	---	Yes	Yes	Yes	Yes	Yes	Yes
Lagged asset allocation controls?	---	Yes	Yes	Yes	Yes	Yes	Yes
Participant controls?	---	---	---	Yes	---	Yes	---
Lagged factor loading controls x Year FEs?	---	---	Yes	Yes	Yes	Yes	Yes
Lagged asset allocation controls x Year FEs?	---	---	Yes	Yes	Yes	Yes	Yes
Participant controls? x Year FEs?	---	---	---	Yes	---	Yes	---
N	29,035	23,489	23,489	21,847	23,489	21,847	698
R2	0.5385	0.5931	0.7003	0.7072	0.0201	0.0247	0.0012

Note: In columns (1)-(6), the unit of observation is ORP participant i in calendar year t, and the sample is the same as in Table 4. Columns (1)-(4) report coefficients and standard errors estimated via pooled OLS regressions. Columns (5)-(6) report coefficients and standard errors estimated via Fama-MacBeth. Columns (1) regresses the after-fee return earned by participant i in calendar year t on a dummy variable indicating whether participant i invests through HIGH, and a separate fixed effect for each calendar year. Columns (2)-(3) control for the fraction of participant i's portfolio allocated to each asset class at the end of calendar year t-1, and the asset-weighted factor loadings of participant i's portfolio at the end of calendar year t-1. Columns (4)-(6) interact the lagged asset allocation and factor loading variables with 11 calendar year fixed effects. Columns (4) and (6) also interact the full set of participant characteristics from Table 3 with 11 calendar year fixed effects. In column (7), the unit of observation is investment j in calendar year t. In the OLS regressions, standard errors are clustered on both participant and calendar year. In the Fama-MacBeth regressions, standard errors are based on the standard deviation of the estimated coefficients in the year-by-year regressions. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 6. How Does Initial Portfolio Composition Differ Between HIGH and LOW?

Panel A. Number of Investments Receiving Positive Allocations in Month 12

	LOW		HIGH		HIGH - LOW	
	# Participants	% Participants	# Participants	% Participants	Without Controls	With Controls
Number of investments = 1	395	19.9%	105	9.8%		
= 2-3	541	27.2%	115	10.7%		
= 4-5	795	40.0%	326	30.4%		
= 6-7	197	9.9%	257	23.9%		
= 8-9	45	2.3%	109	10.1%		
= 10+	15	0.8%	162	15.1%		
All Participants	1,988		1,074			
Mean number of investments	3.62		5.76		2.14 ***	2.25 ***

Panel B. Allocation of Retirement Contribution Across Asset Classes in Month 12

	LOW		HIGH		HIGH - LOW	
Asset Allocation	Average Allocation	% Participants with Allocation = 100%	Average Allocation	% Participants with Allocation = 100%	Average Allocation (without controls)	Average Allocation (with controls)
Fixed Annuity	15.4%	1.5%	7.8%	$\boxed{2.0\%}$	-7.6% ***	-6.1% ***
Money Market	10.6%	$\boxed{9.2\%}$	3.0%	2.6%	-7.5% ***	-9.1% ***
Bonds	9.7%	0.5%	5.7%	0.0%	-4.0% ***	-3.5% ***
Balanced	--	--	6.6%	2.7%		
Domestic Equity	41.2%	3.1%	60.0%	6.7%	18.8% ***	17.9% ***
Foreign	15.8%	1.3%	16.8%	0.6%	1.1%	0.8%
Real Estate	7.3%	0.4%	--	--		
Index Funds	8.1%	1.4%	19.7%	1.1%	11.6% ***	12.4% ***
HIGH Branded Funds	--	--	58.2%	16.8%		

Note: We use data provided by HIGH and LOW on the allocation of retirement contributions across investments to the compare the portfolio composition of ORP participants twelve months after they begin investing through the provider. Because initial investment dates in the LOW asset allocation data are left censored at January 1998, we restrict the sample so that the earliest uncensored observation in month 12 for either provider is February 1999. In Panel A, we summarize the distribution of the number of investment options with positive allocations. We also report the mean number of investment options for LOW and HIGH. In Panel B, we aggregate investment option-level contributions up to seven broad asset classes. We report the average fraction of ORP participant retirement contributions being allocated to each asset class, and the fraction of participants allocating 100% of their contribution to a single asset class. The default investment option for LOW is a money market fund. The default investment option for HIGH is a fixed annuity. HIGH does not offer any real estate investment vehicles. For LOW balanced investments, investment option-level assets are allocated across bonds, domestic equity, and foreign equity. However, we lack the underlying asset allocation data for balanced funds available through HIGH. To test whether values for LOW and HIGH are equal we estimate two regressions. First, we regress the variable of interest on a dummy variable that equals 1 if participant i invests through HIGH. Second, we extend the regression to include the full set of participant characteristics from Table 3, as well as a separate fixed effect for each year-month. All (unreported) standard errors are clustered on year-month. Statistical significant at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 7. Testing for Differences in Factor Loadings Between HIGH and LOW in Month 12

Dependent:	*Beta*			*SMB*		
Sample:	*Participant Portfolios*		*Investment Menus*	*Participant Portfolios*		*Investment Menus*
HIGH	0.2534 ***	0.2537 ***	0.1746 ***	0.1021 ***	0.0992 ***	0.0516 ***
	(0.0162)	(0.0161)	(0.0120)	(0.0065)	(0.0067)	(0.0100)
Date FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Participant controls?	--	Yes	--	--	Yes	--
N	3,061	2,771	10,098	3,061	2,771	10,098
R2	0.2669	0.2997	0.0285	0.3847	0.3994	0.0228
Dependent:	*HML*			*MOM*		
Sample:	*Participant Portfolios*		*Investment Menus*	*Participant Portfolios*		*Investment Menus*
HIGH	0.0468 **	0.0540 **	0.0145	0.0215 ***	0.0206 ***	0.0376 ***
	(0.0232)	(0.0235)	(0.0095)	(0.0055)	(0.0056)	(0.0036)
Date FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Participant controls?	--	Yes	--	--	Yes	--
N	3,061	2,771	10,098	3,061	2,771	10,098
R2	0.332	0.3573	0.0379	0.2806	0.299	0.0476

Note: In this table, we test whether ORP participants investing through HIGH have significantly different factor loadings than those investing through LOW. The sample is the same as in Table 6. We focus on factor loadings of participant i's retirement contribution, twelve months after the initial retirement contribution was directed to HIGH or LOW. Dependent variables in the first column include contribution-weighted average factor loadings estimated from the prior 24 monthly returns using Carhart's (1997) four-factor model. The independent variable of interest is a dummy variable that indicates whether participant i invests through HIGH. In all of the specifications we include a separate fixed effect for each year-month. In half of the specifications we also include the full set of participant control variables from Table 3. In the "Investment Menu" regressions, we switch our focus from the factor loadings of ORP participants to the factor loadings of the investment options available through LOW and HIGH. The unit of observation is fund i in month t. In addition to the dummy variable indicating whether fund i is available through HIGH, we include a separate fixed effect for each year-month. All standard errors are clustered on date. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 8. Testing for Returning Chasing in Choice of Funds, February 1998 - September 2009

Dependent:	Fraction of Retirement Contribution Allocated to Fund i			
Sample Period:	*Month 1 (Month of 1st ORP Contribution)*		*Month 24*	
Sample of Investments:	*All*	*Debt & Equity*	*All*	*Debt & Equity*
Lagged Return * LOW	0.0684 *	0.0655 *	0.0355	0.0271
	(0.0354)	(0.0367)	(0.0312)	(0.0329)
Lagged Return * HIGH	0.0407 ***	0.0416 ***	-0.0015	0.0003
	(0.0054)	(0.0051)	(0.0036)	(0.0034)
Ho: LOW = HIGH	0.3959	0.4859	0.2342	0.4221
Ho: LOW = HIGH = 0	0.0000	0.0000	0.4456	0.7096
Participant controls?	Yes	Yes	Yes	Yes
Fund-level controls?	Yes	Yes	Yes	Yes
Date-by-Provider FEs?	Yes	Yes	Yes	Yes
N	81,742	75,190	74,565	68,429
Adj. R2	0.0804	0.0987	0.0837	0.0923
Incremental R2	0.0037	0.0044	0.0004	0.0003

Note: In this table, we test whether the fraction of retirement contributions allocated to fund j is increasing in the level of fund j's return over the prior 12 months. The sample includes one observation for each investment option available to a HIGH or LOW participant in month t. We estimate one set of regressions in the first month that participant i contributes to HIGH or LOW and another set of regressions in month 24. The independent variables of interest are the lagged after-fee return of fund j interacted with dummy variables indicating whether fund j is available through HIGH or LOW. (No fund is simultaneously available through both providers.) In addition, all regressions include the full set of participant controls from Table 3, lagged factor loadings from Carhart's (1997) four-factor model, and date-by-provider fixed effects. Standard errors are clustered on year-month. We report the p-values of the hypotheses tests that the estimated coefficients on the lagged return variables are equal, and that they are both equal to zero. "Incremental R2" measures the increase in Adj. R2 associated with adding the lagged after-fee return-provider interactions to each regression. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **,

Table 9. Changes to Asset Allocations Differ Between HIGH and LOW During the Recent Financial Crisis?

		Panel A. Investment Horizon = 3 Months				*Panel B. Investment Horizon = 12 Months*			
		1999-2007		2008-2009		1999-2007		2008-2009	
LOW	Increase	1,631	4.3%	507	4.1%	724	8.8%	260	9.3%
	No Change	34,624	91.5%	11,448	91.7%	6,676	81.1%	2,249	80.7%
	Decrease	1,566	4.1%	528	4.2%	828	10.1%	278	10.0%
HIGH	Increase	873	3.5%	90	1.4%	572	10.8%	66	4.7%
	No Change	23,149	93.3%	6,179	96.1%	4,113	77.4%	1,216	86.6%
	Decrease	779	3.1%	158	2.5%	629	11.8%	122	8.7%

	Difference-in-Difference Regressions						Difference-in-Difference Regressions					
	Without Controls			With Controls			Without Controls			With Controls		
Increase	-0.0187	(0.0059)	***	-0.0197	(0.0061)	***	-0.0659	(0.0239)	**	-0.0698	(0.0240)	**
No Change	0.0264	(0.0107)	**	0.0273	(0.0107)	**	0.0965	(0.0276)	***	0.0998	(0.0285)	***
Decrease	-0.0077	(0.0064)		-0.0075	(0.0059)		-0.0306	(0.0175)		-0.0300	(0.0159)	*

Note: In this table, we analyze monthly data from HIGH and LOW on the fraction of participant i's retirement contribution allocated to domestic equity. The sample begins in January 1999 and ends in December 2009. Panels A and B focus on changes in the fraction allocated to domestic equity over 3 and 12 month horizons, respectively. In the top of each panel, we report the fraction of ORP participants that increased, decreased, or made no change to the fraction allocated to domestic equity for each provider and time periods. In the bottom of each panel, we report the interaction term of interest from three difference-in-difference regressions. For example, in the first row, we regress a dummy variable indicating whether participant i increased the allocation to domestic equity in period t on a dummy variable indicating whether participant i invests through HIGH, a dummy variable indicating whether period t falls within 2008-2009, and the interaction between these two independent variables. Regressions "With Controls" include the full set of participant-level controls from Table 3. All standard errors are clustered on the appropriate date (e.g., clustered on calendar year in Panel B). Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table A1. Overview of HIGH and LOW Investment Menus

	LOW		HIGH	
Asset Class	October 1996	December 2009	October 1996	December 2009
Money Market	1	1	1	2
Fixed Annuity	1	1	2	2
Fixed Income	2	2	6	9
Balanced	1	1	5	10
U.S. Equity	2	9	21	31
Global	2	3	5	7
Real Estate	1	2	0	0
Passively Managed	1	2	3	4
Actively Managed	9	17	37	57
Managed by Provider	10	19	16	51
Not Managed by Provider	0	0	24	10
Total Number of Options	**10**	**19**	**40**	**61**

Note: This table summarizes the investment menus available through HIGH and LOW at the beginning and end of our sample period. LOW offers the same ten investment options between October 1996 and June 2007, finally adding nine new investment options in July 2007. In contrast, HIGH makes numerous changes to its investment menu, steadily increasing the number of options from 40 to 61, but also decreasing the number of investment options managed by firms other than HIGH from 24 to 10.