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

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ABSTRACT

Within the Oregon University System's defined contribution retirement plan, one investment provider offers access to face-to-face financial advice through its network of brokers. We find that younger, less highly educated, and less highly paid employees are more likely to choose this provider. To benchmark the portfolios of broker clients, we use the actual portfolios of self-directed investors and counterfactual portfolios constructed using target-date funds, a popular default investment. Broker clients allocate contributions across a larger number of investments than self-directed investors, and they are less likely to remain fully invested in the default option. However, broker clients' portfolios are significantly riskier than self-directed investors' portfolios, and they underperform both benchmarks. Exploiting across-fund variation in broker compensation, we find that broker clients' allocations are higher when broker fees are higher. Survey responses from current plan participants support our identifying assumption that the portfolio choices of broker clients reflect the recommendations of their brokers.

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I. Introduction

Defined contribution retirement plans place important investment decisions in the hands of individuals, many of whom possess limited financial knowledge (e.g., Lusardi and Mitchell (2006)). One approach to improving the quality of individual investment decisions is to invest in educational programs that increase financial literacy (e.g., Bernheim, Garrett, and Maki (2001) and Xu and Zia (2012)). Another approach is to shift investment decisions back onto employers through the use of default investments, such as target-date funds (e.g., Balduzzi and Reuter (2012) and Mitchell and Utkus (2012)). A third approach is to have employers provide individuals with access to financial advice via financial intermediaries. In this paper, we ask whether access to financial advice is an effective substitute for financial literacy or for the use of defaults.[1]

Providing financial advice to investors is a multi-billion dollar industry. However, given the volatility of investment returns, it can be difficult for investors—even the subset who are financially literate—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 additional benefit to investors. Therefore, while it is clear that financial advisors are compensated for providing advice, it is unclear whether and how investors benefit from this advice.[2] The best case is that financial advisors help their clients construct well-diversified portfolios and avoid common financial mistakes. The worst case is that financial advisors bias their investment recommendations to maximize their compensation at the expense of their clients' portfolios. The challenge that arises when trying to measure the impact of financial advisors on their clients' portfolios is the need to determine what the portfolios would have been in the absence of any investment advice.

To shed new light on this important issue, we study the impact of financial advisors on the retirement portfolios of a large sample of public college and university employees. Our data come from the Oregon University System's Optional Retirement Plan (ORP), a portable defined

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[1] Technically, the broker clients that we study receive "financial guidance" rather than "financial advice." However, because we argue in Appendix A that this distinction is not meaningful in our setting, we follow the existing literature and refer to broker recommendations as "financial advice."

[2] Reuter and Zitzewitz (2006) study mutual fund recommendations published in personal finance publications. They find evidence that recommendations increase fund-level flows, but also that recommendations favor advertisers. Bhattacharya, Hackethal, Kaesler, Loos, and Meyer (2012) study the impact of unbiased advice on investor behavior. They offer unbiased advice to a random sample of investors in "one of the biggest brokerages in Europe." Although they show that advice improves the portfolios of those who follow it, only 5% of investors accept the offer to receive advice and, even among this subset of investors, the unbiased advice is rarely followed.

contribution retirement plan introduced in October 1996 as an alternative to the state's traditional defined benefit retirement plan. Notably, ORP participants can choose to invest through a firm that uses a network of brokers to provide personal face-to-face financial services.[3] Between October 1996 and October 2007, approximately one-third of ORP participants choose the high-service investment provider, which we refer to as HIGH. The other two-thirds of ORP participants choose to invest through three lower-service investment providers, the most popular of which we refer to as LOW. With the help of Oregon University System, we were able to match administrative data on investor characteristics with account-level data from HIGH and LOW.[4]

Our empirical strategy for evaluating broker recommendations is to compare the actual portfolios of broker clients (HIGH) to the actual portfolios of self-directed investors (LOW) and to counterfactual portfolios based on an implementable strategy using target-date funds (TDFs). The comparison with self-directed investors is motivated by the idea that brokers with access to HIGH's investment menu should be able to help their clients construct and maintain portfolios that are "at least as good" as those constructed by self-directed investors in LOW. The comparison with counterfactual portfolios based on TDFs is motivated by the fact they became popular default investment options following the passage of the Pension Protection Act of 2006, and by our conjecture that many broker clients would "choose" the default investment option in the absence of brokers. Indeed, consistent with our conjecture, Mitchell and Utkus (2012) conclude that demand for TDFs within 401(k) plans reflects an underlying demand for financial advice. The implicit assumption underlying both comparisons is that the portfolio choices of broker clients reflect the recommendations of their brokers. Therefore, before testing for differences in investor portfolios, we test for differences in the demographic characteristics and survey responses of investors who self-select into HIGH versus LOW.

Using administrative data, we find that ORP participants who choose HIGH tend to be younger, less highly educated, and less highly paid than those who choose LOW. Because financial sophistication has been shown to increase with age, educational attainment, and income, these differences suggest that demand for brokers is higher when financial sophistication is

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[3] Benartzi (2001), Benartzi and Thaler (2001), and Agnew et al. (2003) study asset allocation decisions within 401(k) plans, which traditionally have not provided access to financial advisors. Barber and Odean (2000) study the behavior of 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.

[4] As we show in Table 1, 82.5% of ORP participants choose to invest through either HIGH or LOW. We lack account-level data for participants who chose to invest through the other two ORP providers, SMALL and SMALLER because these providers were dropped from ORP on November 2007.

lower.[5] To provide additional insights into the choice between HIGH and LOW, we use data from a survey that the Oregon University System sent to ORP participants in April 2012. Specifically, we compare the responses of 791 participants who faced the choice between HIGH (297) and LOW (494) during our sample period. We find strong evidence that demand for HIGH is driven by demand for broker recommendations. Investors who choose HIGH are significantly more likely to rank access to face-to-face meetings with financial advisers as important or very important (70% for HIGH versus 39% for LOW). They are also significantly more likely to claim that they relied upon the recommendation of a broker when determining their allocation to equity (74% versus 45%). And, even among the subset of respondents who report having an ongoing relationship with a financial advisor, investors who choose HIGH are much less likely to agree with the statement: "I would feel comfortable making changes to my equity and bond balance without consulting my adviser" (25% versus 44%). The survey evidence also argues against demand for HIGH versus LOW being driven by differences in investment menu sizes or differences in investor risk aversion.

We compare HIGH and LOW investors' portfolios along several dimensions. When we focus on annual after-fee returns earned between 1999 and 2009, we find that broker clients underperform self-directed investors, on average, by slightly more than the 0.89 percent paid in broker fees. This finding, consistent with both Bergstresser, Chalmers and Tufano (2009) and Karabulut and Hackethal (2010), highlights the fact that self-directed investors benefit from not having to pay broker fees. More provocatively, we find that both sets of investors significantly underperform the counterfactual portfolios based on target-date funds. This is true for 71.0% of the investor-year observations involving broker clients and 63.1% of the investor-year observations involving self-directed investors. In other words, while we cannot conclude that broker clients would have earned higher returns if they had been forced to construct their own portfolios in the absence of a default investment option, the majority of them would have benefited from being defaulted into target-date funds.

When we switch our focus to portfolio risk, we find that broker clients bear significantly more market risk, on average, than self-directed investors, but that broker clients only bear slightly more market risk than if they had invested in target-date funds. Interestingly, when we

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[5] Georgarakos and Inderst (2010) model the impact of financial literacy, trust in financial advice, and legal rights on stock market participation. In their model, demand for financial advice falls with the level of financial literacy.

use the predicted probability of choosing HIGH to construct a proxy for the lack of financial so-phistication, we find that the correlation between financial sophistication and portfolio risk dif-fers sharply across the two providers.[6] Among self-directed investors, lower predicted values are associated with significantly lower betas, but among broker clients, lower predicted values are associated with significantly higher betas. These patterns may reflect mistakes on the part of self-directed investors, opportunistic behavior on the part of brokers, or both.

When we turn to asset allocation and fund selection decisions, the evidence is mixed. On the one hand, broker clients hold more funds (5.8 versus 3.6), allocate significantly more of their portfolio 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%). These differences suggest that, in exchange for paying broker fees, broker clients receive advice on how to construct well-diversified portfolios. On the other hand, when we study the initial allocation of retirement contributions across avail-able funds, we find that HIGH investors are more likely than LOW investors to invest in funds with high past returns. Exploiting across-fund variation in the level of broker fees, we find that funds paying higher broker fees receive economically and statistically significantly higher re-tirement contributions from broker clients. This finding provides further support for our assump-tion that broker clients' portfolios reflect the recommendations of their brokers. It also comple-ments the evidence in Hackethal, Inderst, and Meyer (2011) and Christoffersen, Evans, and Musto (2012), Anagol, Cole, and Sarkar (2012), and Mullainathan, Nöth, and Schoar (2012) highlighting the agency conflicts that can arise when financially unsophisticated investors seek advice from financial intermediaries. Collectively, the findings in our paper suggest that, within the context of an employer-sponsored retirement plan, investors may benefit more from a care-fully chosen default investment option than from access to a financial advisor.

The remainder of the paper is organized as follows. In Section II, we identify the demo-graphic characteristics that explain the choice between HIGH and LOW. We also present survey evidence that demand for face-to-face financial advice plays an important role in the choice be-tween HIGH and LOW. In Section III, we describe the account-level data for HIGH and LOW, and test for differences in annual returns, portfolio risk, asset allocation, and fund selection. In

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[6] Calvet, Campbell, and Sodini (2009) combine financial wealth, family size, and educational attainment into a fi-nancial sophistication index, and show that higher values of this index are associated with fewer financial mistakes. The mistakes they consider are underdiversification, failure to rebalance, and the disposition effect. Behrman, Mitchell, Soo, and Bravo (2010) find that financial literacy has a casual impact on wealth accumulation, and that this impact increases with educational attainment.

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 Access to Brokers?

A. Institutional Details

In October 1996, OUS introduced a defined contribution plan, known as the Optional Retirement Plan (ORP). The goal was to provide a portable alternative to the defined benefit plan being offered to public employees, known as the Public Employees Retirement System (PERS). When ORP was introduced, existing OUS faculty and administrators had to make a "one-time, irrevocable" choice between ORP and PERS.[7] Similarly, new OUS faculty and administrators had to choose between ORP and PERS six months after they are hired.

In this paper, we study the retirement portfolio choices and outcomes of OUS employees who actively choose ORP over PERS.[8] 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 brokers to provide relatively *high* levels of "personal face-to-face service." In contrast, LOW, SMALL and SMALLER are more representative of investor-directed providers available through other defined contribution retirement plans in that they charge lower fees but provide less personalized 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 OUS payroll data to identify provider choices between October 1996 and October 2007, we see that 31.7% choose HIGH and 50.7% choose LOW.[9]

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[7] 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. However, due to data limitations discussed below, much of our analysis focuses on OUS employees hired after 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 brokers on retirement savings rates.

[9] Because OUS switched payroll systems in 1998, the 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.

B. Participant Characteristics by Retirement Plan Choice

Investors may value access to brokers because they have lower levels of financial literacy, derive utility from the one-on-one relationship, or both. An expanding literature links differences 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 not representative 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 helpful to keep this caveat in mind. Another important caveat is that we are studying the subset of employees who choose ORP, the defined contribution plan, over PERS, the defined benefit plan.

In Table 2, we describe four samples of OUS employees, sorted into groups based on the (one-time, irreversible) retirement plan choices that they made between October 1996 and October 2007. Columns (1) and (2) describe ORP participants who chose to invest through HIGH versus LOW. Studying the choice between HIGH and LOW allows us to determine which demographic characteristics predict demand for brokers, which is one of our main research questions. Column (3) describes the full sample of employees who choose to participate in ORP, while column (4) describes the full sample of employees who choose to participate in PERS (or who are defaulted into PERS). Studying the choice between ORP and PERS allows us to determine which demographic characteristics lead employees to select out of our sample. This comparison is motivated by the fact that investors with lower levels of financial literacy may be more likely to forgo a defined contribution plan in favor of a defined benefit plan (Brown and Weisbenner (2007)).

The participant characteristics we summarize in Table 2 include monthly salary (only available for those choosing ORP), gender, age, ethnicity (reported for 88.5% of ORP participants), and educational attainment at the time of employment (reported for 67.6% of ORP participants). We also report the fraction of participants classified as research faculty (i.e., job classification includes the string "Teach/Res") and the fraction that are employed within a "quantitative department" (i.e., organizational description includes a reference to business, computer sciences, engineering, life sciences, mathematics, physical sciences, or social sciences).

Univariate comparisons between HIGH and LOW reveal three patterns. First, HIGH participants earn significantly lower monthly salaries than LOW 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 HIGH decreases with educational attainment. Overall, these differences suggest that—even within our relatively homogenous sample of faculty and administrators—demand for brokers falls with income, age, and education.[10] However, in contrast to studies that find lower levels of financial literacy among females and minorities (e.g., Lusardi and Mitchell (2007b) and Lusardi and Tufano (2009)), we find only modest evidence that demand for access to a broker varies with gender or ethnicity.

When we switch our focus to univariate comparisons between ORP and PERS, we find evidence suggesting that demand for the defined contribution plan also responds to the level of financial literacy. Specifically, we find that demand for ORP increases with educational attainment. It is also significantly higher for research faculty members, and for those employed within more quantitative departments. This suggests that there may be less variation in financial literacy within our sample of ORP participants than there is within the full sample of OUS employees (or the subsample that selects into PERS). Indeed, our survey of current participants reveals an unusually high level of financial literacy within our sample.

C. Predicting Demand for Brokers

To identify factors that predict demand for access to brokers we estimate two sets of probit regressions in Table 3. In columns (1), (2), and (3), the dependent variable equals one if participant i's initial ORP retirement contribution is directed to HIGH and zero otherwise. The sample is restricted to the 82.5% of ORP participants who choose HIGH or LOW. The sample is further restricted in columns (2) and (3) to participants for whom the date of the initial ORP contribution is not left censored at January 1999. Focusing on the subsample of participants for whom we can observe the month of the choice between HIGH and LOW allows us to control for economic conditions that vary with the month of the choice, and for changes in the relative size of the investment menus. We report marginal effects, along with standard errors clustered on the month of the choice.

We begin, in column (1), by focusing on salary, gender, and age because these are char-

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[10] 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 overview of the literature on financial literacy and retirement behavior.

acteristics that we observe for the vast majority of ORP participants. (Note that we use this specification to predict the probability of choosing HIGH, which we use in later tables.) Consistent with the univariate comparisons, we find that demand for brokers falls with salary, is highest for those under the age of 30 (the omitted category), and is largely uncorrelated with gender. When we turn our attention to the campus fixed effects, we find that demand for HIGH is significantly lower at Oregon State University, the Office of the Chancellor, and the three regional campuses than at University of Oregon (the omitted category). The lower demand for brokers at Oregon State University, which houses the engineering 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 the three regional campuses—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 restrict our sample to participants for whom we observe data on ethnicity. In column (3), we further restrict our sample to participants (and campuses) for whom we observe data on educational attainment. 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 significant. Interestingly, we find that demand for HIGH is 19.3 percentage points lower at Oregon State University and 8.6 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

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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 in both columns, and statistically significant at the 5-percent level in column (2). This is one piece of evidence that the typical ORP participant is choosing HIGH for access to brokers rather than for access to a larger investment menu.

To explore the impact of recent equity market movements on the demand for a financial advisor, we control for the return on the S&P 500 index over the prior 12 months and for the value of the Chicago Board Options Exchange Market Volatility Index (VIX) at the beginning of the month.[11] Our prediction is that demand for brokers will be higher when recent equity market returns have been lower or more volatile because investors will be more sensitive to downside risk. However, we find little empirical support for either prediction.

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 investment recommendations from brokers.

Brown and Weisbenner (2007) study the choice between DB and DC 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 (expected) levels of financial literacy are more likely to choose LOW over HIGH. In columns (4) and (5), we study the choice between PERS and ORP. As suggested by the univariate comparisons in Table 2, we find that demand for PERS is lower when participants are more highly educated, and when they work in more quantitative departments. Interestingly, we also find that demand for PERS is lower when equity markets are less volatile, suggesting that recent volatility makes investors more sensitive to the market risk that a defined contribution plan entails.

D. Survey Evidence on the Demand for HIGH versus LOW

OUS emailed a survey to the 3,588 current participants of the Optional Retirement Plan in April 2012. While the survey was primarily intended to measure participant satisfaction with

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[11] Chalmers and Reuter (2012) find that payout choices by PERS retirees respond to both measures.

existing plan design and to solicit feedback on several potential changes, we were able to add questions related to the use of brokers, financial literacy, and risk aversion. Of the 1,380 (38%) completed survey responses, 791 are from ORP participants who chose either HIGH (297) or LOW (494) during our sample period. The survey responses for these investors provide a window into the minds of investors who faced the choice between different investment providers. (The fact that the survey did not require completion of all questions explains the variation in sample size from question to question.) The caveat is that we are asking participants to explain how they made decisions as far back as October 1996.

Table 4 Panel A begins to address the identifying assumption in our paper that investors choosing HIGH are doing so because they want brokers to help them make financial decisions. It reveals that investors who originally chose HIGH are significantly more likely to have "an on-going relationship with a financial adviser" (58.7% versus 32.7%; p-value of 0.000), and significantly less likely to agree or strongly agree with the statement "I would feel comfortable making changes to my equity and bond balance without consulting my adviser" (24.7% versus 43.8%; p-value of 0.000). Moreover, when asked how they primarily decided upon the fraction of their portfolio to invest in equity, those choosing HIGH were significantly more likely to select the "recommendation of an adviser" (74.3% versus 45.3%; p-value of 0.000).

Panel B reveals that 84.9% of HIGH investors meet with a broker at least once a year. It also reveals that those investing through HIGH are more likely to implement advice quickly (43.4% versus 24.6%) and less likely to ignore advice (8.2% versus 17.0%) than those investing through LOW. Interestingly, only 23.3% of HIGH investors agree or strongly agree with the statement "I understand how much money my adviser earns on my account." Panel C reinforces the idea that HIGH investors seek investment advice. Consistent with the prediction in Gennaioli, Shleifer, and Vishny (2012), it also reveals that HIGH investors seek "peace of mind" from an advisor that they can trust.

Panel D describes the weights that ORP participants place on investment provider characteristics. Investors who originally chose HIGH place significantly more weight on "Access to face-to-face meetings with a financial adviser" when choosing between investment providers. While 39.3% of LOW investors rate face-to-face meetings as important or very important, the fraction is 69.9% of HIGH investors (p-value of 0.000). (Investors who chose HIGH were asked to evaluate the statement "meeting with my broker gives me peace of mind." Within this sample,

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76.8% choose agree or strongly agree.) In contrast, menu choice is unlikely to be a first-order issue in provider selection. While slightly more HIGH investors rate "The number of equity fund choices available" as important or very important (57.4% versus 55.7%; p-value of 0.653), the difference is neither economically large nor statistically significant. The fact that HIGH investors place slightly less weight on recent fund returns when choosing between providers (80.8% versus 87.3%; p-value of 0.015) is interesting in light of the evidence below that they are more likely to chase recent returns when choosing which funds to invest in.

Finally, Panel E reveals only modest differences in financial literacy and risk aversion. To measure financial literacy we include three questions that Lusardi and Mitchell (2006) created for use in the HRS (on compounding, inflation, and the risk associated with investing in a single stock versus a stock mutual fund), plus an additional question on compounding. For each participant, we calculate the fraction of correct answers. While Lusardi and Mitchell (2006) find that only one-third of respondents were able to correctly answer all three of their questions, the fraction is significantly higher among our sample of younger, more highly educated investors. Specifically, 90.0% of HIGH investors answered all four questions correctly versus 93.3% of LOW investors. While the 3.3% difference is statistically significant at the 5-percent level (p-value of 0.034), it is not economically large. In other words, to the extent that demand for a financial advice is driven by variation in financial literacy, that variation does not show up in the answers to standard financial literacy questions. To measure risk aversion, we borrow a question from "HRS 2006 – Module 2" that asks individuals to choose between "Job 1" (which guarantees them their current total lifetime income) and "Job 2" (which is equally likely to cause their total lifetime income to go up by $x\%$ or to go down by $y\%$). We find no statistically significant evidence that LOW investors are more risk averse than HIGH investors.

III. Differences in Asset Allocation and Performance Between HIGH and LOW

A. Identification

Our goal is to estimate the casual impact of brokers on their clients' portfolios. The challenge is that, during most of our sample period, investors can choose whether to invest through a broker. Moreover, the findings in the previous section suggest that broker clients place greater value on financial advice than self-directed investors, perhaps because broker clients are less experienced investors.

For the purposes of evaluating investor's choices—and outcomes that follow from these choices—we exploit the fact that investors differ along two dimensions. First, some investors value financial advice, while others do not. Second, some investors receive and follow financial advice, while others do not. We summarize these differences based on the answers to two questions: *{Does investor i value financial advice?, Does individual i receive and follow financial advice?}*. The typical broker client is described by *{Yes, Yes}*, while the typical self-direct investor is described by *{No, No}*. Let Y_{it} be the choice (or outcome associated with a previous choice) of investor *i* in year *t*. We can use account-level data on self-directed investors to make inferences regarding $E[Y|\{No, No\}]$. For example, this is the approach taken in Odean (1998), Odean (1999), Barber and Odean (2000), and Barber and Odean (2001). Similarly, we can use account-level data on broker clients to make inferences regarding $E[Y|\{Yes, Yes\}]$, although these data have been relatively scarce. The challenge, especially when studying the behavior of brokers' clients, is to identify an appropriate benchmark.

One possibility is to benchmark the portfolios of broker clients against the portfolios of self-directed investors:

$$E[Y|\{Yes, Yes\}] - E[Y|\{No, No\}]. \tag{1}$$

When Y_{it} is a measure of portfolio risk, this difference measures how much more or less risk broker's clients choose to bear than self-directed investors. When Y_{it} is the risk-adjusted, after-fee return earned by investor *i* in year *t*, this difference measures the extent to which broker clients underperform self-directed investors.

Comparisons of broker clients to self-directed investors allow us to assess the quality of the guidance that brokers offer to their clients. On the one hand, brokers 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, and less likely to naively chase past investment returns. If broker services and financial literacy are perfect substitutes, HIGH and LOW investors should both exhibit optimal behavior, with differences in average performance due entirely to the broker fees that HIGH investments charge to compensate their brokers. On the other hand, there may be agency conflicts between brokers and their clients. For example, just as Reuter and Zitzewitz (2006) find that the financial media en-

courages return chasing and churning by publishing monthly articles that tout recent winners, brokers may encourage their clients to invest in actively managed funds with high past returns. Or, as Carlin (2009) argues, brokers may exploit their clients' lower levels of financial literacy by recommending riskier investments—a strategy that makes it easier to mask underperformance.[12]

Comparing the portfolios of broker clients to those of self-directed investors is a reasonable way to evaluate brokers. However, to measure the causal impact of broker recommendations on investors who actively seek out those recommendations, one needs to estimate:

$$\text{E}\,[Y\,|\,\{Yes,Yes\}] - \text{E}\,[Y\,|\,\{Yes,No\}], \tag{2}$$

which compares the choices of broker clients to the counterfactual choices that they would have made in the absence of access to brokers.

We consider two proxies for $\text{E}\,[Y\,|\,\{Yes,No\}]$. First, we construct counterfactual portfolios based on target-date retirement funds (TDFs), which automatically reduce an investor's exposure to market risk as he get closer to his target retirement date. Because the Pension Protection Act of 2006 encourages the use of TDFs as default investment options within defined contribution retirement plans, this proxy allows us to test whether TDFs are an effective substitute for brokers. Our identifying assumption is that investors who chose to invest through a broker would have "chosen" to invest in the default investment option in the absence of access to brokers.[13] Second, we consider investors who we predict should value financial advice, but who are not investing through a broker. Because much of this variation comes from across-campus differences in the average demand for brokers, our identifying assumption is that it reflects variation in the availability or quality of the broker, rather than across-campus differences in the average level of investment experiment or financial literacy. In the next draft of this paper, we will instead exploit exogenous variation in the availability of brokers by comparing participants who are able to choose HIGH, because they became eligible to participate in ORP by October 2007, to participants who we predict would have chosen HIGH but are not able to do so, because they became eligible to participate in ORP after October 2007. Note that the only other paper of which we are aware that attempts to estimate the causal impact of brokers is Mullainathan, Nöth,

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[12] Our survey evidence that HIGH and LOW investors exhibit similar levels of risk aversion allows us to rule out the potential alternative that difference levels of risk taking follow from different levels of risk aversion.
[13] When OUS changed the set of ORP providers in November 2007, it introduced Fidelity target date funds as the default investment option.

and Schoar (2012), which uses an audit study approach to measure the recommended changes to prospective clients' pre-existing portfolios.

Finally, to measure the causal impact of unsolicited financial advice on self-directed investors, one needs to estimate:

$$\text{E}\,[Y\,|\,\{No,Yes\}] - \text{E}\,[Y\,|\,\{No,No\}]. \tag{3}$$

The difference will be positive if the advice moves the self-directed investor towards the optimal portfolio, and negative if it moves her away from the optimal portfolio. It will be zero if the advice is unbiased but the self-directed investor is already holding the optimal portfolio. Therefore, the more financially literate the self-directed investors, the smaller the expected benefit of providing unsolicited unbiased advice. Note that this is the causal effect estimated by the experiment in Bhattacharya et al. (2012). In this paper, we are interested in estimating the differences described by equations (1) and (2).

When comparing the portfolios of HIGH and LOW investors, our implicit assumptions are that HIGH investors rely on broker recommendations and LOW investors do not. The survey responses in Table 4 suggest a less perfect dichotomy; some LOW investors have ongoing relationships with financial advisers and some HIGH investors do not. Nevertheless, the survey evidence increases our confidence that, on average, investors who chose HIGH are doing so to implement the recommendations that they receive during face-to-face meetings with their brokers.[14] Comparisons between HIGH and LOW are also 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 to access to brokers will nevertheless choose HIGH so that they can invest in, for example, the HIGH International Equity Fund. One argument against this possibility is that every ORP participant who invests through HIGH is paying for personalized service in the form of broker fees ranging from 55 to 105 basis points—even if they choose not to interact with a broker. In other words, for those who do not value broker services, access to the HIGH investment menu comes at a significant cost. In addition, the survey evidence we presented above suggests that demand for HIGH is driven much more by the desire for face-to-face interactions with a broker than by perceived differences in

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[14] In our conversations with LOW executives, we learned that less than four percent of the approximately three million LOW investors with a retirement account balance less than $500,000 (a set that includes all but two ORP participants) choose to speak with a LOW retirement consultant in any given year. Moreover, we learned that LOW did not begin to actively offer financial guidance to LOW participants until 2006.

investment menus.

C. 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.

To calculate the annual after-fee return of participant i in year t, we combine data on participant i's dollar holdings of each investment option at the beginning of year t with data on the after-fee returns earned by each investment option 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. To calculate participant i's exposure to a risk factor in year t, we weight the estimated factor loading of investment j at the beginning of year t by the fraction of her portfolio allocated to investment j at the beginning of year t. For investment j in year t, we estimate factor loadings using the prior 24 monthly returns. We consider a one-factor model based on CAPM, a four-factor model based on Carhart (1997), and a five-factor model that adds the excess return on the MSCI Barra EAFE index, to capture exposure to international equity. To calculate risk-adjusted returns for participant i in year t, we subtract off the expected return on each factor, obtained by multiplying each portfolio's estimated factor loading at the beginning of year t by the return of the factor during year t.

D. Comparing Portfolio Risk and Returns

To assess the impact of brokers on portfolio risk and return, we begin by comparing the

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annual after-fee returns of broker clients (HIGH) and self-directed investors (LOW). We find, in Table 5, that HIGH investors underperform LOW investors by 1.54 percent (1.81 percent versus 3.35 percent). A significant fraction of this difference can be explained by the fact that HIGH investors pay, on average, 0.89 percent of their assets each year in broker fees. However, the 1.54 percent average difference masks significant time-series variation in relative performance. HIGH investors earn significantly higher average after-fee returns when U.S. equity markets post strong positive returns (1999, 2003, and 2009) and significantly lower annual after-fee returns when U.S. equity markets post strong negative returns (2000, 2001, 2002, and 2008). These patterns suggest that HIGH investors bear significantly more systematic risk than LOW investors. Indeed, when we switch our focus from annual after-fee returns to portfolio risk, we find that the average CAPM beta is 0.832 for HIGH investors and 0.618 for LOW investors. One interpretation is that broker clients bear too much market risk. Another is that self-directed investors bear too little market risk. (Our survey evidence argues against the interpretation that differences in portfolio risk reflect differences in risk aversion.)

As an alternative benchmark, we consider counterfactual portfolios constructed from target-date funds (TDFs).[15] To determine participant i's counterfactual allocation to TDFs, we assume that her target retirement date is the year in which she turns 65. Because Fidelity had the largest market share among TDF providers at the beginning of our sample period (Balduzzi and Reuter (2012)), we restrict the counterfactual investment options to Fidelity Freedom funds. When the target retirement year is less than or equal to 2010, we allocate 100% of her portfolio to the Fidelity Freedom 2010 fund. When the target retirement year is greater than or equal to 2040, we allocate 100% of her portfolio to the Fidelity Freedom 2040 fund. For target retirement years between 2011 and 2039, we allocate portfolio assets to the Fidelity Freedom fund(s) with the target retirement date(s) closest to the participant's target retirement date. For example, when the target retirement date is 2029, we allocate 10% of the portfolio to the Fidelity Freedom 2020 fund and 90% to the Fidelity Freedom 2030 fund. Because allocations to TDFs are determined entirely by investor age, variation in counterfactual portfolios across HIGH and LOW investors

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[15] Target-date funds invest in both equity and debt, but shift their asset allocation toward debt as the investor ages. For example, in March 2012, the Fidelity Freedom 2020 fund allocated 57% of its portfolio to equity, 37% debt and 6% cash. At the same time, the Fidelity Fredom 2040 fund allocated 87% to equity and 17% to debt. Target date retirement funds have become popular default investments 401(k) plans since the passage of the Pension Protection Act of 2006, which lists target-date funds among the set of qualified default investment alternatives (QDIA).

is driven by variation in the distribution of investor ages.[16]

Table 5 reveals two interesting facts about the TDF benchmarks. First, they earn higher after-fee returns than the actual portfolios of HIGH or LOW investors. This is true for 71.0% of the investor-year observations for HIGH and 63.1% of the investor-year observations for LOW. The outperformance is due to the fact that TDFs offered investors lower exposure to market risk during the start of our sample period and higher exposure to market risk during the end of our sample period. Second, the average CAPM betas of the counterfactual TDF portfolios are 0.753 for HIGH and 0.763 for LOW, which are slightly lower than the average CAPM betas of 0.832 for HIGH investors.

To shed more light on differences in portfolio risk and return, we turn to multivariate regressions in Table 6. Each regression includes the same set of explanatory variables. To measure the average difference in risk or return between HIGH and LOW, we include a dummy variable indicating whether participant i invests through HIGH in year t. We also include the predicted value from the probit predicting whether participant i invests through HIGH (from column (1) of Table 3) interacted with dummy variables indicating whether participant i invests through HIGH or LOW. The use of the predicted value is motivated by Calvet, Campbell, and Sodini (2009); the interaction terms allow us to determine whether investors who are predicted to rely upon a broker and do so hold different portfolios than investors who are predicted to rely upon a broker but do not. To control for time-series variation in aggregate market returns, we include a separate dummy variable for each calendar year. Because the predicted value of choosing HIGH is constant for participant i, and because participant i's portfolio choices are likely to be highly correlated across years, standard errors are clustered on participant.

We begin, in column (1), by testing for differences in the annual returns of actual portfolios. In Panel A, the coefficient on HIGH indicates that broker clients earn annual after-fee returns that are 1.39 percent lower than those earned by self-directed investors (p-value of 0.000). In Panel B, when we add broker fees back to the annual returns of broker clients, the return difference falls to 0.47 percent (p-value of 0.156). In other words, whether broker clients underperform self-directed investors depends on whether we view broker fees as compensation for advice

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[16] Because we construct a new counterfactual portfolio for each participant each year, we are implicitly assuming that participants who invest in two different TDFs rebalance their portfolio annually. Since this is unlikely to happen in practice, it is worth noting that our findings are similar when we restrict participants to invest in a single target-date fund over our entire sample period.

or as compensation for superior investment performance.

Broker clients underperform self-directed investors by similar amounts, in column (3), when we subtract the counterfactual portfolio returns from actual portfolio returns.[17] This is because the counterfactual portfolio returns are quite similar in the two samples. The constant term in column (3) implies that self-directed investors, on average, underperformed TDFs by 1.83 percent (p-value of 0.000). The fact that counterfactual portfolios based on TDFs outperform the actual portfolios of both broker clients and self-directed investors suggests that TDFs are a reasonable default investment option.

Next, we test for differences in portfolio risk. When we focus on actual portfolios in column (4), we find interesting differences in how portfolio risk varies with the predicted probability of choosing HIGH. The higher this predicted probability, the higher the exposure to market risk among broker clients but the lower the exposure to market risk among self-directed investors. (Both coefficients are statistically significant at the 1-percent level.) To the extent that higher predicted probabilities reflect lower levels of financial literacy or investment experience, these estimates suggest that brokers significantly increase the market risk exposure of less savvy investors. When we focus on TDF-based portfolios, the coefficients on both interaction terms are positive and statistically significant from zero (at the 1-percent level). These positive coefficients reflect that fact that younger investors are more likely to choose HIGH and, because their target retirement dates are more distant, their counterfactual portfolios have larger allocations to equity. It is worth noting, however, that we find the same basic pattern in column (3), when we subtract the CAPM betas of the counterfactual portfolios from the CAPM betas of the actual portfolios, as we find in column (1), when we focus on the CAPM betas of the actual portfolios. In column (6), a one standard deviation increase in the probability of choosing HIGH is predicted to increase the CAPM beta of broker clients by 0.112 and decrease the CAPM beta of self-directed investors by 0.099—a economically and statistically significant difference of 0.211. These differences are consistent with brokers tilting their clients toward higher beta investments

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[17] 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. When we switch our focus to the annual after-fee returns earned by investment j in calendar year t, we find (in unreported regressions) that investments available through HIGH underperform by approximately 0.47 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.

to more readily mask underperformance, but also with Gennaioli, Shleifer, and Vishny's (2012) prediction that brokers reduce the disutility associated with bearing financial risk. Regardless, Mitchell and Utkus' (2012) finding that the introduction of TDFs into 401(k) retirement accounts increases equity exposure the most for those workers aged 34 and younger suggests that TDFs are a less expensive way to increase risk-taking by less experienced investors.

Finally, we test for differences in risk-adjusted returns. When annual returns are measured net of broker fees, we find that the one-factor alphas earned by broker clients are 92 basis points lower than those earned by self-directed investors (p-value of 0.003). Karabulut and Hackethal (2010) also find that financial advice is associated with lower risk-adjusted returns. In addition, we find that broker clients underperform by 100 basis points when actual risk-adjusted returns are benchmarked against the risk-adjusted returns of TDFs.[18] In fact, when we focus on annual risk-adjusted returns, we find that TDFs earn higher after-fee alphas in 75.1% of the investor-year observations involving broker clients versus 62.1% of the investor-year observations involving self-directed investors.

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

In this section, we compare the asset allocation decisions of HIGH and LOW investors, with the goal of identifying margins along which brokers plausibly impact investor behavior. 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 7, 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 significant at the 1-percent level. The larger number of investments in the typical HIGH portfolio raises the possibility that brokers 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 brokers) to allocate retirement contributions across more investments for reasons unrelated to optimal asset alloca-

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[18] Broker clients underperform by 125 basis points when we switch to the four-factor model and 143 basis points when we switch to the five-factor model. When we restrict the sample to those individuals for whom we are able to estimate the full selection model (column (3) in Table 3), broker clients underperform by between 125 and 161 basis points. Each of these estimates is statistically significant at the 1-percent level.

tion.[19]

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.[20] These differences help to explain the different levels of systematic risk that we documented in Table 5. 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.

To control for the different dates on which the initial asset allocation decisions are made, and the different demographic characteristics of HIGH and LOW investors, we estimate the following OLS regression:

$$allocation_{it} = \alpha + \lambda HIGH_{it} + \beta X_{it} + \eta_t + \varepsilon_{it} \tag{4}$$

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 report the estimated coefficient on the HIGH dummy variable in the rightmost column of table 7. We find that all of the differences—except for the allocation to foreign assets—are statistically significant at the 1-percent level. Interestingly, in these tests, 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

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[19] 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. Morrin et al. (2012) find that the number of funds in which participants choose to invest increases when LOW increases the number of investment options from 10 to 19, from about 3.5 funds to 5.0 funds.

[20] 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.

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 brokers (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 brokers 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. Another explanation, which we test below, is that brokers guide investors toward those funds paying the highest broker fees.

Finally, Madrian and Shea (2000) find that a substantial fraction of retirement plan participants "choose" to invest in the default investment option. Therefore, brokers 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, the difference increases from 7.2 to 7.6 percentage points and is statistically significant at the 1-percent level. Given our survey evidence that HIGH investors are more likely to rely upon broker recommendations when deciding on their asset allocation, this difference is likely to reflect the causal impact of brokers.

F. 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 8, 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. There are two differences relative to Table 6, where we document differences in CAPM betas. First, we now use lagged monthly asset allocation data—rather than lagged account balance data—to convert investment-level factor loadings into asset-weighted

portfolio-level factor loadings.[21] Second, we consider factor loadings from a five-factor model, which includes the excess return on the U.S. market (Beta), the excess return on EAFE, the small minus big mimicking portfolio (SMB), the high minus low mimicking portfolio (HML), and the momentum portfolio (MOM).

To test for differences in factor loadings, we regress the portfolio-level factor loading for participant i in month t on the HIGH dummy variable. One set of specifications includes the full set of demographic control variables reported in column (2) of Table 3. Another set of specifications include the predicted probability of choosing HIGH interacted with the HIGH and LOW dummy variables. Again, HIGH portfolios have larger loadings on domestic equity (estimated using the one-factor beta or the five-factor beta) than LOW portfolios. And, again, the estimated coefficients on the interaction terms are of opposite signs and economically and statistically significant. HIGH portfolios also have larger loadings on international equity, size, book-to-market, and momentum, implying that HIGH investors hold systematically riskier investments than LOW investors. One possibility is that HIGH brokers intentionally guide their clients toward riskier investments. Another possibility is that the HIGH investment menu is tilted toward riskier investments and brokers do not take this tilt into account when making recommendations.

In the remaining columns of Table 8, 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 domestic equity, international equity, size, and momentum than LOW investments. However, the estimated coefficients on domestic equity and size 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 survey evidence that the average level of risk aversion is similar for HIGH and LOW, we find it more plausible that brokers steer HIGH investors toward specific types of investments than that HIGH investors inherently prefer these types of investments.

G. Comparing the Investment Selection of HIGH and LOW Investors

To implement an asset allocation plan, an investor must allocate her monthly retirement

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

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.[22] At the same time, because studies like Carhart (1997) find little evidence that abnormal returns persist, investors should not allow recent returns to distort their asset allocation decisions. In Table 9, we explore the impact of brokers on investment selection by testing whether return-chasing behavior is stronger among self-directed investors. We also use across-fund variation in broker fees in the HIGH investment menu to test whether HIGH clients are more likely to allocate their retirement dollars to investments paying higher broker fees. This variation allows us to test for the agency conflict that can arise when financially unsophisticated (or trusting) investors seek advice from financially sophisticated intermediaries.

Our dependent variable is the fraction of participant i's retirement contribution that is allocated to fund j in month t. Because this variable is nonnegative, estimation is via Tobit. The sample consists of all ORP participants for whom the enrollment date is uncensored, and all funds are available to HIGH or LOW investors in month t. There are three independent variables of interest. To test for return chasing, we include 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. To test for possible agency conflicts, we include the fee that fund j pays each year to the broker. For HIGH investments, the broker fee is a constant 55, 85 or 105 basis points; for LOW investments, the broker fee is zero. To test whether investors are sensitive to the level of fund fees more broadly, we include the annual fees charged by the fund that are not paid to the broker (i.e., the total annual fee minus the broker fee). Interacting "Not Broker Fee" with dummy variables indicating whether the fund is available to HIGH or LOW investors allows us to test whether brokers steer investors away from fees from which the brokers do not benefit. We control for the fund's broad asset category and lagged factor loadings, and for the full set of participant-level controls from Table 3. Because we are testing for differential sensitivities to lagged returns and fees across ORP providers, we also include a separate fixed effect for each provider each month, so that we are comparing fund returns and fees within each menu relative to the other funds within the same menu. Standard errors are clustered on date.

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

In columns (1) through (3), we focus on asset allocations in the first month that we observe an ORP retirement contribution. The coefficient estimates on past returns are positive and statistically significant, suggesting that both HIGH and LOW investors take recent returns into consideration when selecting funds. However, the sensitivity is stronger for HIGH investors, and all differences between HIGH and LOW are statistically significant (with p-values ranging between 0.000 and 0.051). In other words, fund selection by investors with access to brokers is more sensitive to recent returns than fund selection by self-directed investors. For HIGH investors, a one-standard deviation increase in past returns is predicted to increase the allocation to investment j by 8.9 percentage points. For LOW investors, the predicted change is only 1.5 percentage points.

Perhaps more provocatively, the investment decisions of HIGH investors are increasing in the level of the broker fees. The magnitude is economically significant. A 50 basis point increase in broker fees (i.e., the difference between the lowest and highest broker fee) is predicted to increase the allocation to investment j by 17.2 percentage points.[23] Interestingly, we also find robust evidence that HIGH investors invest less in funds that have high fees that are not retained by the broker. This suggests that brokers steer investors away from high fee funds when those fees do not benefit the brokers.

In columns (4) through (6), we focus to how retirement contributions are allocated across funds 24 months after the initial retirement contributions were made. The evidence of return chasing behavior is much weaker, especially for HIGH investors. Therefore, to the extent that brokers help investors chase past returns, they only provide this service when determining the initial asset allocation. The fact that broker fees continue to explain HIGH investment choices in month 24 reflects the fact that broker fees paid by investment j do not vary in the time-series. Inferences are similar when we focus on a narrower set of asset classes.

IV. Conclusion

We use unique investor-level data from the Oregon University System to study the impact of financial advisors on portfolio choice. We have three main findings. First, we document significant differences between those investors who choose to invest through brokers and those

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[23] Using fund-level data for a large sample of broker-sold mutual funds, Christoffersen, Evans, and Musto (2012) find evidence that higher broker fees drive fund-level flows. Using account-level data from a single bank, Hackethal, Inderst, and Meyer (2011) find evidence that advisor recommendations respond to sales incentives.

who do not. Employees choosing to invest through a broker are younger, less highly educated, and less highly paid. They are also more likely to state that they chose HIGH to meet face-to-face with a broker, and that they relied upon their broker's recommendations when deciding how to invest. Importantly, demand for HIGH does not appear to be driven by differences in risk aversion or the larger investment menu that comes bundled with access to a broker.

Second, we document interesting differences in portfolio choices. The fact that broker clients pay an average of 0.89 percent in broker fees each year helps to explain their underperformance, relative to self-directed investors, of 1.54 percent. Since the average broker clients' retirement account balance is $34,416, this corresponds to an average annual "tax" of $530. In exchange for these fees, broker clients are moved out of the default fixed annuity and into funds with higher-than-average past returns, higher-than-average exposure to several forms of market risk, and that pay higher-than-average broker fees. These findings highlight the agency conflict that can arise when unsophisticated investors seek investment advice from financial intermediaries. They also highlight the fact that, on average, brokers do not help investors construct portfolios that are "at least as good" as the portfolios constructed by self-directed investors. In this sense, financial literacy dominates financial advice.

Third, because HIGH investors are different than LOW investors, we do not know how they would have invested if they had been forced to invest through LOW. However, we are able to show that the majority of the broker clients (and self-directed) investors in our sample would have earned significantly higher annual after-fee returns from being defaulted into target-date funds. And, it seems likely that those investors most likely to choose to invest through a financial advisor are the same investors who are the most likely to accept the default investment option in the absence of access to a financial advisor. Therefore, the utility that investors receive from face-to-face meetings with financial advisors would need to be substantial to justify the use of agency-conflicted financial advisors over sensible default investment options.

Appendix A. 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.[24] To comply with ERISA, HIGH uses algorithms developed by Ibbotson Associates to generate financial advice for investors with managed accounts. However, OUS prohibits 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 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 brokers 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 brokers.[25]

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[24] 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.

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

Appendix B. 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, October 1996 - October 2007

Date Range	LOW	HIGH	SMALL	SMALLER	TOTAL
10/96 - 01/99	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 401(a) ORP 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. Participant Summary Statistics, by Plan Choice

Sample:	Subset of ORP		All ORP	All PERS
	HIGH	LOW		
	(1)	(2)	(3)	(4)
Sample Size	1,843	2,946	5,807	18,023
Monthly Salary (mean)	$3,892	$4,796	$4,399	-
Monthly Salary (median)	$3,460	$4,097	$3,823	-
% missing data	*1.6%*	*0.9%*	*1.2%*	*100.0%*
Female	49.9%	44.8%	47.8%	53.3%
% missing data	*3.7%*	*5.5%*	*4.6%*	*6.1%*
Age < 30	19.8%	12.2%	16.0%	28.0%
30 <= Age < 40	35.4%	39.7%	37.7%	24.3%
40 <= Age < 50	26.1%	27.8%	27.0%	20.2%
50 <= Age	18.7%	20.3%	19.3%	27.5%
% missing data	*3.7%*	*5.5%*	*4.6%*	*6.1%*
Faculty	51.8%	57.7%	54.9%	42.1%
Quantitative Department	21.8%	23.1%	23.2%	13.7%
% missing data	*6.4%*	*8.5%*	*7.7%*	*0.0%*
Asian	7.2%	8.0%	7.8%	6.2%
Black	2.9%	2.5%	2.5%	2.4%
Hispanic	3.4%	3.5%	3.2%	4.2%
White	84.1%	84.3%	84.7%	84.7%
Other	2.4%	1.6%	1.8%	2.5%
% missing data	*8.7%*	*13.3%*	*11.5%*	*13.4%*
PhD	39.4%	58.9%	49.3%	22.2%
Masters	32.3%	26.7%	29.2%	39.5%
Bachelors	28.3%	14.4%	21.4%	38.3%
% missing data	*29.7%*	*35.1%*	*32.4%*	*50.1%*

Note: In this table, we use administrative data to summarize the samples of ORP and PERS
participants. ORP is the defined contribution retirement plan introduced in October 1996 as
an alternative to PERS, the traditional defined benefit retirement plan. Gender, job status,
ethnicity and educational attainment are measured in the month that the participant begins
working for OUS. Faculty is a dummy variable that indicates whether participant i's job
classification includes the string "Teach/Res". Quantitative is a dummy variable that indicates
whether the participant's organizational description includes a reference to business, computer
sciences, engineering, life sciences, mathematics, medicine, physical sciences, or social
sciences. We have the fewest missing values when we focus on salary and the most missing
values when we focus on educational attainment (because these data are only collected by a
subset of campuses). Because the administrative data on the date of the choice between plans
is left censored at January 1999, age and salary are measured in either the month of the actual
choice between plans or in January 1999.

Table 3. Sample Selection, February 1999 - October 2007

Dependent: Sample:	1 if ORP participant chooses HIGH HIGH or LOW			1 if OUS employee chooses PERS PERS or ORP	
	(1)	(2)	(3)	(4)	(5)
Salary	-0.0361 ***	-0.0358 ***	-0.0262 ***		
	(0.0035)	(0.0052)	(0.0066)		
Female	0.0022	-0.0013	-0.0298	0.0028	-0.0112
	(0.0129)	(0.0204)	(0.0277)	(0.0068)	(0.0102)
Age [30, 40]	-0.1049 ***	-0.1191 ***	-0.0766 **	-0.1277 ***	-0.0688 ***
	(0.0192)	(0.0245)	(0.0313)	(0.0183)	(0.0185)
Age [40, 50]	-0.0708 **	-0.1122 ***	-0.0789 **	-0.0816 ***	-0.0054
	(0.0313)	(0.0245)	(0.0369)	(0.0166)	(0.0180)
Age [50, 100]	-0.0384	-0.1212 ***	-0.0717	0.0240 *	0.1055 ***
	(0.0632)	(0.0287)	(0.0443)	(0.0120)	(0.0169)
Asian		0.0528	0.1049 ***	-0.0151	0.0135
		(0.0329)	(0.0377)	(0.0120)	(0.0166)
Black		0.0431	0.0417	-0.0606 ***	-0.1062 ***
		(0.0617)	(0.0834)	(0.0233)	(0.0362)
Hispanic		-0.0041	0.0251	0.0316 **	0.0393 *
		(0.0457)	(0.0578)	(0.0139)	(0.0214)
Other		0.0817	0.0081	0.0159	-0.0168
		(0.0683)	(0.0824)	(0.0195)	(0.0346)
Quantitative		0.0025	-0.0108	-0.0772 ***	-0.0347 ***
		(0.0223)	(0.0259)	(0.0138)	(0.0137)
PhD			-0.2012 ***		-0.2243 ***
			(0.0297)		(0.0328)
Masters			-0.1120 ***		-0.0292
			(0.0285)		(0.0194)
Return of S&P 500 index over prior 12 months		0.0696	-0.1422	0.0911	0.1060
		(0.1066)	(0.1175)	(0.1349)	(0.1789)
Lagged value of VIX		0.2584	-0.3198	0.5808 **	0.9455 **
		(0.2439)	(0.3009)	(0.2403)	(0.3727)
Ratio of number of options in HIGH and LOW		-0.0047	-0.0793 **		
		(0.0209)	(0.0388)		
Campus: Oregon State	-0.1348 ***	-0.1409 ***	-0.1933 ***	0.0166	0.0354 *
	(0.0281)	(0.0274)	(0.0309)	(0.0152)	(0.0210)
Campus: Portland State	-0.0022	0.0161	-0.0136	0.1231 ***	0.1320 ***
	(0.0196)	(0.0298)	(0.0345)	(0.0122)	(0.0179)
Campus: Oregon Inst. of Technology	0.0854	-0.0691	-0.0861	0.0186	-0.0026
	(0.0954)	(0.0537)	(0.0597)	(0.0215)	(0.0362)
Campus: Eastern Oregon	-0.0355	-0.1014 *		0.0674 ***	
	(0.0593)	(0.0515)		(0.0174)	
Campus: Southern Oregon	-0.1279 ***	-0.1803 ***		0.1317 ***	
	(0.0424)	(0.0399)		(0.0159)	
Campus: Western Oregon	-0.0358	-0.1292 **		0.0656 ***	
	(0.0739)	(0.0524)		(0.0165)	
Office of the Chancellor	-0.1456 *	-0.2095 ***		-0.0777	
	(0.0632)	(0.0576)		(0.0511)	
N	4,503	2,760	1,703	16,395	8,091
Pseudo-R2	0.0433	0.0564	0.0765	0.0670	0.0928

Note: In this table, we study two different levels of sample selection. Since we are primarily interested in contrasting the behavior of
        investors in HIGH and LOW, in columns (1), (2), and (3), we predict the choice between HIGH and LOW. The sample includes the
        subset of ORP participants who choose to invest through either HIGH or LOW. Since choices before February 1999 are coded as
        January 1999, in columns (2) and (3) we restrict the sample to those choosing between February 1999 and October 2007. The
        dependent variable equals one if ORP participant i chooses HIGH over LOW. In columns (4) and (5), we study the choice between
        PERS and ORP. The sample includes all OUS employees who face the choice between ORP and PERS between February 1999 and
        October 2007. The dependent variable equals one if employee i chooses PERS over ORP. Demographic controls include salary,
        gender, age, ethnicity (the omitted category is "White), and educational attainment (the omitted category is "Bachelors"). To control
        for potential differences in preferences across employers, we include a fixed effect for each of the seven campuses, and for the Office
        of the Chancellor. To control for economic conditions, we control for both the return on the S&P 500 index over the prior 12 months,
        and for the value of the VIX index at the beginning of the month of the choice. In columns (2) and (3), we control for the participant's
        monthly salary and the ratio of the sizes of the investment menu available from HIGH and LOW. The smaller sample sizes in columns
        (2) and (4) reflect the fact that three campuses and the Office of the Chancellor did not collect data on educational attainment. The
        table reports marginal effects estimated via probit. Standard errors are clustered on the date of the choice. Statistical significance at
        the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 4. Evidence on the demand for HIGH versus LOW from a survey of current ORP participants

Panel A. Testing for differences in reliance upon financial adviser when deciding on asset allocation

	Do you have an ongoing relationship with a financial adviser?		"I would feel comfortable making changes to my equity and bond balance without consulting my adviser"		How did you **primarily** decide on the fraction to invest in stocks?			
						My own research and knowledge of investing	Recommendation of adviser	Recommendation of friends, family, or co-workers
	N	Yes	N	Agree or Strongly Agree	N			
LOW	452	32.7%	144	43.8%	369	44.7%	45.3%	10.0%
HIGH	259	58.7%	146	24.7%	214	21.5%	74.3%	4.2%
Difference		26.0%		-19.1%		-23.2%	29.0%	-5.8%
P-value		0.000		0.001		0.000	0.000	0.012

Panel B. Information on how often participants meet with HIGH, the relative speed with which they implement advice, and how well they understand broker compensation

How Often Do You Meet With Your HIGH Adviser?		When you receive investment advice, do you usually implement the advice:				"I understand how much money my adviser earns on my account"	
			LOW	HIGH			
Never	15.1%	"Within two weeks"	24.6%	43.4%		Strongly Agree	8.1%
Once a year	55.7%	"Within two months'	34.6%	30.9%		Agree	15.2%
Twice a year	21.7%	"Within the year"	23.9%	17.6%		Disagree	51.2%
More than twice	7.6%	"Never"	17.0%	8.2%		Strongly Disagree	25.6%
N	212	N	419	233		N	211

Panel C. Information on the services that investors receive from meeting with HIGH brokers

"My adviser's expertise in deciding how much of my investments to put in the stock market is very valuable"		"The most important factor in choosing my adviser is that I trust him or her"		"Meeting face to face with my adviser gives me peace of mind in my investments"		"My adviser calms me down when the market is volatile"	
Strongly Agree	25.2%	Strongly Agree	29.3%	Strongly Agree	32.9%	Strongly Agree	14.0%
Agree	51.0%	Agree	47.3%	Agree	44.0%	Agree	41.1%
Disagree	18.5%	Disagree	17.1%	Disagree	18.4%	Disagree	37.2%
Strongly Disagree	5.3%	Strongly Disagree	6.3%	Strongly Disagree	4.8%	Strongly Disagree	7.7%
N	206	N	205	N	207	N	207

Panel D. Testing for differences in factors that influenced choice of ORP investment provider

| | When choosing between ORP investment providers assess the importance of the following factor: | | | | | | | |
| | Access to face to face meetings with a financial adviser | | The number of equity fund choices available | | The level of fund expenses | | Historical investment performance | |
	N	Important or Very Important	N	Important or Very Important	N	Important or Very Important	N	Important or Very Important
LOW	489	39.3%	488	55.7%	490	73.5%	494	87.3%
HIGH	296	69.9%	291	57.4%	295	72.5%	297	80.8%
Difference		30.7%		1.7%		-0.9%		-6.4%
P-value		0.000		0.653		0.777		0.015

Panel E. Testing for differences in risk aversion and financial literacy

| | Financial Literacy | | Choice between jobs with certain versus uncertain income | | | | | |
| | | Fraction of Four Financial Literacy Questions Correct | | Fraction Who Prefer Job 2 50% up 20% 50% down 15% | | Fraction Who Prefer Job 2 50% up 20% 50% down 10% | | Fraction Who Prefer Job 2 50% up 20% 50% down 5% |
	N		N		N		N	
LOW	401	93.3%	285	20.0%	268	47.8%	311	83.9%
HIGH	240	90.0%	164	17.7%	162	45.1%	176	77.3%
Difference		-3.3%		-2.3%		-2.7%		-6.6%
P-value		0.034		0.547		0.587		0.072

Notes   OUS sent a link to an online survey to all 3,588 current ORP participants in April 2012. In this table, we analyze the responses of the 791 participants who chose HIGH (297) or LOW (494) between October 1996 and October 2007. The survey response rates are similar for these two groups of investors: 16.1% (297/1843) for HIGH and 16.8% (494/2946) for LOW. For each question, we analyze all non-missing answers. P-values are estimated using standard errors that are robust to heteroscedasticity.

Table 5. Comparing Actual Portfolios to Counterfactual Portfolios Based on Target-Date Funds, 1999-2009

Panel A. HIGH

| | Actual | | Actual | Target-Date Fund Benchmark | |
	Annual Return	Beta	Broker Fee	Annual Return	Beta
1999	29.25%	0.787	0.931	23.79%	0.732
2000	-13.78%	0.878	0.926	-2.41%	0.721
2001	-18.84%	1.087	0.933	-8.70%	0.710
2002	-17.99%	0.993	0.926	-13.29%	0.676
2003	23.27%	0.829	0.920	24.39%	0.672
2004	8.96%	0.796	0.911	9.45%	0.699
2005	4.59%	0.828	0.906	7.81%	0.757
2006	10.05%	0.795	0.907	11.84%	0.795
2007	4.81%	0.755	0.851	8.69%	0.802
2008	-31.59%	0.727	0.848	-33.45%	0.833
2009	25.00%	0.754	0.857	29.05%	0.822
1999-2009	1.81%	0.832	0.898	4.79%	0.753

Panel B. LOW

| | Actual | | Actual | Target-Date Fund Benchmark | |
	Annual Return	Beta	Broker Fee	Annual Return	Beta
1999	20.59%	0.733	0.000	24.27%	0.743
2000	-8.42%	0.739	0.000	-2.61%	0.731
2001	-11.32%	0.731	0.000	-8.79%	0.716
2002	-14.94%	0.713	0.000	-13.49%	0.683
2003	21.03%	0.626	0.000	24.79%	0.686
2004	9.13%	0.618	0.000	9.49%	0.705
2005	6.44%	0.602	0.000	7.87%	0.763
2006	11.33%	0.589	0.000	11.84%	0.796
2007	8.35%	0.600	0.000	8.69%	0.802
2008	-24.71%	0.577	0.000	-33.45%	0.834
2009	16.70%	0.536	0.000	29.06%	0.823
1999-2009	3.35%	0.618	0.000	5.05%	0.767

Note: In this table, we compare the actual portfolios of broker clients (HIGH) and self-directed investors (LOW) to counterfactual portfolios based on four Fidelity target-date retirement funds. We also report the average broker fee being paid by broker clients. The sample includes all investors for whom we observe positive holdings of at least one investment at the beginning of yeat t. To determine a participant's counterfactual asset allocation, we assume that her target retirement date is the year in which she turns 65. When the target retirement year is less than or equal to 2010, we allocate 100% of her portfolio to the Fidelity Freedom 2010 fund. When the target retirement year is greater than or equal to 2040, we allocate 100% of her portfolio to the Fidelity Freedom 2040 fund. For target retirement years between 2011 and 2039, we allocate dollars to the Fidelity Freedom fund(s) with the target retirement date(s) closest to the participant's target retirement date. For example, when the target retirement date is 2030, we allocate 100% to the Fidelity Freedom 2030 fund. When the target retirement year is 2025, we allocate 50% to the Fidelity Freedom 2020 fund and 50% to the Fidelity Freedom 2030 fund. "Annual Return" is the average annual buy-and-hold return that the participant's (actual or counterfactual) portfolio would earn in year t based on his or her allocation across investment options at the beginning of year t. "Beta" is the average CAPM beta of the participants' (actual or counterfactual) portfolios at the beginning of year t, based on the participant's allocations across investments at the beginning of year t.

Table 6. Testing for Differences in Risk and Return, HIGH versus LOW versus Target-Date Funds, 1999-2009

Dependent:	Annual Portfolio Return			CAPM Beta			CAPM Alpha		
	Actual	TDF	Actual - TDF	Actual	TDF	Actual - TDF	Actual	TDF	Actual - TDF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Annual portfolio returns net of HIGH broker fees									
HIGH?	-0.0140 ***	-0.0014 *	-0.0126 ***	-0.0682	-0.0309	-0.0373	-0.0092 ***	0.0007	-0.0100 ***
	(0.0033)	(0.0007)	(0.0033)	(0.0525)	(0.0189)	(0.0532)	(0.0031)	(0.0005)	(0.0031)
Predicted Pr(HIGH) * HIGH?	0.0009	0.0026	-0.0018	0.3882 ***	0.1215 ***	0.2667 **	-0.0095	-0.0035 ***	-0.0060
	(0.0071)	(0.0016)	(0.0070)	(0.1091)	(0.0377)	(0.1088)	(0.0065)	(0.0010)	(0.0064)
Predicted Pr(HIGH) * LOW?	0.0027	0.0003	0.0023	-0.1974 ***	0.0767 ***	-0.2742 ***	0.0036	-0.0023 ***	0.0059 **
	(0.0031)	(0.0008)	(0.0031)	(0.0576)	(0.0282)	(0.0613)	(0.0029)	(0.0006)	(0.0029)
Constant	0.0275 ***	0.0459 ***	-0.0183 ***	0.7233 ***	0.7504 ***	-0.0272	-0.0066 ***	0.0078 ***	-0.0144 ***
	(0.0012)	(0.0003)	(0.0012)	(0.0213)	(0.0103)	(0.0227)	(0.0011)	(0.0002)	(0.0011)
Ho: Interactions equal	0.8168	0.2061	0.5899	0.0000 ***	0.3408	0.0000 ***	0.0650 *	0.2993	0.0921 *
N	19,371	19,371	19,371	19,371	19,371	19,371	19,371	19,371	19,371
R2	0.8239	0.9823	0.2529	0.1269	0.1905	0.1984	0.1912	0.8968	0.1710
Panel B. Annual portfolio returns gross of HIGH broker fees									
HIGH?	-0.0048	-0.0014 *	-0.0035				-0.0001	0.0007	-0.0008
	(0.0033)	(0.0007)	(0.0033)				(0.0031)	(0.0005)	(0.0031)
Predicted Pr(HIGH) * HIGH?	0.0004	0.0026	-0.0023				-0.0099	-0.0035 ***	-0.0064
	(0.0072)	(0.0016)	(0.0070)				(0.0065)	(0.0010)	(0.0065)
Predicted Pr(HIGH) * LOW?	0.0027	0.0003	0.0024				0.0036	-0.0023 ***	0.0059 **
	(0.0031)	(0.0008)	(0.0031)				(0.0029)	(0.0006)	(0.0029)
Constant	0.0275 ***	0.0459 ***	-0.0183 ***				-0.0066 ***	0.0078 ***	-0.0144 ***
	(0.0012)	(0.0003)	(0.0012)				(0.0011)	(0.0002)	(0.0011)
Ho: Interactions equal	0.7689	0.2061	0.5484				0.0577 *	0.2993	0.0819 *
N	19,371	19,371	19,371				19,371	19,371	19,371
R2	0.8233	0.9823	0.2484				0.1739	0.8968	0.1524

Note: The unit of observation is the portfolio of ORP participant i in calendar year t. The sample period is 1999-2009. The dependent variable in column (1) is the annual portfolio return estimated using the participant's actual investment holdings at the beginning of year t. Column (2) switches to annual portfolio returns estimated using counterfactual target-date fund holdings, while column (3) subtracts the counterfactual annual returns from the actual annual returns. The dependent variables in columns (4), (5), and (6) are portfolio-level betas estimated from the CAPM betas of actual and counterfactual holdings. Similarly, the dependent variables in columns (7), (8), and (9) are portfolio-level alphas estimated using portfolio-level factor loadings at the beginning of year t and annual factor returns during year t. The independent variables include a dummy variable indicating whether participant i invests through HIGH, the predicted probability that participant i invests through HIGH interacted with the dummy variable indicating whether participant i invests through HIGH, the predicted probability that participant i invests through HIGH interacted with the dummy variable indicating whether participant i invests through LOW, and a full set of calendar year fixed effects. The predicted probabilities are based on the specification in column (1) of Table 3, which controls for salary, gender, age, and campus. In Panel A, the annual portfolio returns of broker clients (HIGH) are measured net of broker fees. In Panel B, the annual portfolio returns of broker clients (HIGH) are measured gross of broker fees. (The target-date fund returns in columns (2) and (5) are unchanged.) Standard errors are clustered on participant i. We report the p-value from the test that the coefficients on the two interaction terms are equal. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 7. 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%	2.0%	-7.6% ***	-6.1% ***
Money Market	10.6%	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 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 8. Testing for Differences in Factor Loadings Between HIGH and LOW in Month 12

Dependent:	Beta from one-factor model				Beta from five-factor model			
Sample:	Participant Portfolios			Investment Menus	Participant Portfolios			Investment Menus
HIGH	0.3185 ***	0.3125 ***	0.1673 **	0.1582 ***	0.2284 ***	0.2227 ***	0.0894 *	0.1057 ***
	(0.0295)	(0.0299)	(0.0651)	(0.0134)	(0.0184)	(0.0183)	(0.0462)	(0.0169)
Predicted Pr(HIGH) * HIGH?			0.1963 *				0.2022 **	
			(0.1163)				(0.0905)	
Predicted Pr(HIGH) * LOW?			-0.1859 **				-0.1455 **	
			(0.0733)				(0.0655)	
Date FEs?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Participant controls?	--	Yes	--	--	--	Yes	--	--
N	2,736	2,736	2,736	10,098	2,736	2,736	2,736	10,098
R2	0.3475	0.3674	0.3503	0.0193	0.2765	0.2977	0.2797	0.0115

Dependent:	EAFE				SMB			
Sample:	Participant Portfolios			Investment Menus	Participant Portfolios			Investment Menus
HIGH	0.0392 ***	0.0398 ***	0.0291	0.0768 ***	0.0980 ***	0.0970 ***	0.1160 ***	0.0549 ***
	(0.0117)	(0.0112)	(0.0180)	(0.0100)	(0.0072)	(0.0071)	(0.0155)	(0.0100)
Predicted Pr(HIGH) * HIGH?			-0.0043				-0.0417	
			(0.0432)				(0.0360)	
Predicted Pr(HIGH) * LOW?			-0.0328 *				0.0006	
			(0.0190)				(0.0131)	
Date FEs?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Participant controls?	--	Yes	--	--	--	Yes	--	--
N	2,736	2,736	2,736	10,098	2,736	2,736	2,736	10,098
R2	0.1694	0.1833	0.1701	0.0465	0.3712	0.3798	0.3719	0.029

Dependent:	HML				MOM			
Sample:	Participant Portfolios			Investment Menus	Participant Portfolios			Investment Menus
HIGH	0.0394 *	0.0452 *	0.1099 ***	-0.0072	0.0105 *	0.0094 *	-0.0113	0.0209 ***
	(0.0232)	(0.0233)	(0.0366)	(0.0110)	(0.0057)	(0.0055)	(0.0120)	(0.0050)
Predicted Pr(HIGH) * HIGH?			-0.1499 **				0.0446	
			(0.0663)				(0.0291)	
Predicted Pr(HIGH) * LOW?			0.0184				-0.0077	
			(0.0274)				(0.0095)	
Date FEs?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Participant controls?	--	Yes	--	--	--	Yes	--	--
N	2,736	2,736	2,736	10,098	2,736	2,736	2,736	10,098
R2	0.2933	0.3126	0.2963	0.0407	0.231	0.2469	0.2331	0.0587

Note: In this table, we test whether ORP participants investing through HIGH have significantly different factor loadings than those investing through LOW. The sample of investors is the same as in Table 6, except that we focus on each participant once, twelve months after his or her 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 two models. In the first model, the only factor is the excess return on the market, as reported on Kenneth French's website. In the second model, there are five factors: the four factors from Carhart (1997), as reported on Kenneth French's website, plus the excess return on the MSCI Barra EAFE index. The independent variables include a dummy variable indicating whether participant i invests through HIGH, the predicted probability that participant i invests through HIGH interacted with the dummy variable indicating whether participant i invests through HIGH, the predicted probability that participant i invests through HIGH interacted with the dummy variable indicating whether participant i invests through LOW, and a separate fixed effect for each date. The predicted probabilities are based on the specification in column (1) of Table 3, which controls for salary, gender, age, and campus. A subset of the specifications separately include the full set of demographic controls from column (3) of 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 9. Modeling Allocation of Retirement Contributions Across Funds, February 1998 - September 2009

Dependent:	Fraction of Retirement Contributions Allocated to Fund j					
Sample Period:	*Month 1 (1st ORP Contribution)*			*Month 24*		
Sample of Investments:	*All*	*Debt & Equity*	*Equity*	*All*	*Debt & Equity*	*Equity*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Lagged Return * LOW	0.224 **	0.133 *	0.218 *	0.300 ***	0.143	0.107
	(0.093)	(0.077)	(0.120)	(0.102)	(0.103)	(0.161)
Not Broker Fee * LOW	0.182	-0.139	-1.194 ***	-0.468 ***	-0.880 ***	-0.662 ***
	(0.181)	(0.179)	(0.461)	(0.099)	(0.123)	(0.159)
Lagged Return * HIGH	0.448 ***	0.443 ***	0.448 ***	-0.073	-0.038	-0.012
	(0.045)	(0.043)	(0.049)	(0.051)	(0.047)	(0.056)
Not Broker Fee * HIGH	-0.280 ***	-0.253 ***	-0.271 ***	-0.245 ***	-0.262 ***	-0.312 ***
	(0.011)	(0.010)	(0.013)	(0.012)	(0.013)	(0.028)
Broker Fee	0.455 ***	0.406 ***	0.386 ***	0.436 ***	0.442 ***	0.376 ***
	(0.029)	(0.030)	(0.027)	(0.055)	(0.055)	(0.056)
N	72,163	66,881	39,208	66,839	62,011	36,127
Adj. R2	0.2038	0.2217	0.2859	0.1853	0.1782	0.2369

Note: In this table, we test whether the fraction of retirement contributions allocated to fund j responds to the level of fund j's return over the prior 12 months, the level of fund j's fees that are paid to a broker, and the level of fund j's fees that are not paid to a broker. The sample includes one observation for each investment option available to a HIGH or LOW participant in month t. We estimate one set of Tobit regressions in the first month that participant i contributes to HIGH or LOW and another set of TOBIT 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, the broker fee associated with fund j (which is zero from LOW), and the fund's annual fee minus the broker fee. (No fund is simultaneously available through both providers.) In addition, all regressions include the full set of participant controls and campus FEs from column (3) of Table 3, lagged factor loadings from Carhart's (1997) four-factor model extended to include the excess return on the MSCI Barra EAFE index, and date-by-provider fixed effects. We exclude participants who allocate 100% of their retirement contribution to the default investment option. Standard errors are clustered on the month of the choice. 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. 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

Asset Class	LOW		HIGH	
	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, both increasing the total number of investment options, but also decreasing the number of investment options managed by firms other than HIGH.