Is Conflicted Investment Advice Better than No Advice?*

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ABSTRACT

The value that brokers generate depends on both the quality of their investment recommendations and their clients' counterfactual portfolios. To identify counterfactual portfolios inside a defined contribution retirement plan, we exploit time-series variation in access to brokers. When brokers are available, the correlations with age, income, and educational attainment suggest that brokers are chosen by participants who value advice on asset allocation and fund selection because they are less financially sophisticated. When brokers are no longer available, demand for target-date funds (TDFs), which combine portfolio management with asset allocation, increases differentially among participants with the highest predicted demand for brokers. We find that broker client portfolios earn significantly lower risk-adjusted returns and Sharpe ratios than matched portfolios based on TDFS—due in part to broker commissions that average 0.90% per year—but offer similar levels of risk. Exploiting across-fund variation in the level of broker fees, we find that broker clients allocate more dollars to high-fee funds. This finding increases our confidence that actual broker client portfolios reflect broker recommendations, and it highlights an agency conflict that can be eliminated when TDFs replace brokers.

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I. Introduction

Providing financial advice to investors is a multi-billion dollar industry. Because investment returns are volatile, however, it can be difficult for investors—even those who are financially sophisticated—to distinguish good recommendations from bad. This fact raises important questions about the quality of the recommendations that investors receive from their advisors, as does the likelihood that demand for recommendations is inversely related to an investor's level of financial sophistication.[1] Anagol, Cole, and Sarkar (2013), Christoffersen, Evans, and Musto (2013), Hackethal, Inderst, and Meyer (2012), and Mullainathan, Nöth, and Schoar (2012) use a variety of empirical strategies to show that advisor recommendations reflect advisors' self-interests.[2] These papers raise interesting questions about whether and how broker recommendations can be improved. However, the decision to seek broker recommendations in the first place raises important, unanswered questions about the portfolios that broker clients would have held in the absence of advice. Our empirical setting allows us to provide evidence that addresses the causal effect of broker recommendations relative to this elusive counterfactual.

The difficulty in defining the counterfactual portfolios challenges researchers studying the benefits of advisors.[3] This is the case because clients benefit from receiving and following broker recommendations when the expected utility of doing so (net of fees) exceeds the expected utility of investing on their own. Everything else equal, this difference in expected utilities depends on the quality of the broker recommendations that they follow. However, broker clients may rationally prefer biased recommendations to no recommendations. This is because the difference in expected utilities also depends on how the clients would have invested in the absence of broker recommendations. The lower the expected utility associated with a client's counterfactual portfolio, the more likely that the client is to benefit even from biased recommendations—

[1] 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. Inderst and Ottaviani (2012) and Calcagno and Monticone (2014) model interactions between financial advice, financial literacy, and potential policy interventions.

[2] Bergstresser, Chalmers, and Tufano (2009) and Del Guercio and Reuter (2014) show that broker-sold mutual funds underperform direct-sold funds. Hoechle, Ruenzi, Schaub, and Schmid (2013) study broker advised trades versus self-determined trades in a Swiss bank for given individuals. The evidence is that broker influenced trades display inferior performance.

[3] See for example, Hung and Yoong (2013) who articulate the limitations of "advice" studies in many contexts due to selection and reverse causality. They use survey data complemented with controlled lab experiments to assess the usefulness of advice. They argue that the selection effects from financial literacy are not significant. {p. 191} In their experiments they find unsolicited advice does not affect investment behavior, while optional advice is taken up by those with lower financial literacy and outcomes in terms of asset allocation are improved. See also Foerster, Linnainmaa, Melzer and Previtero (2014) who find advisors affect behavior but do not improve performance.

such as to invest in those actively managed mutual funds paying high broker fees. For example, in Gennaioli, Shleifer, and Vishny (2015), brokers increase their clients' expected utility by increasing equity allocations above counterfactual levels; the high broker fees follow directly from the large gains to trade. On the other hand, the higher the expected utility associated with a client's counterfactual portfolio, the lower the potential benefit from receiving and following biased (or unbiased) recommendations.

An ideal experiment would withhold recommendations from a random set of real world investors who seek to invest through a broker. To measure the causal effect of broker recommendations on portfolio returns, risk levels, and expenses, we would then use the actual portfolios of these reluctantly self-directed investors to identify the counterfactual portfolios of the broker clients. Our empirical strategy is similar in that we use time-series variation in investor access to brokers to identify the counterfactual portfolios of broker clients.

Our empirical setting is the Oregon University System's (OUS) Optional Retirement Plan (ORP), a defined contribution retirement plan introduced in October 1996, as an alternative to the defined benefit retirement plan covering other state employees.[4] When joining ORP, participants choose the investment provider to which their retirement contributions will be sent. Between October 1996 and October 2007, the four providers were offered to participants: HIGH, whose network of brokers provide face-to-face recommendations, and three participant-directed options: LOW, SMALL, and SMALLER.[5] Beginning in November 2007, HIGH, SMALL and SMALLER are no longer available to new participants. New participants can choose between LOW or NEW, neither of which provide the same type of personalized attention that HIGH did. Our empirical strategy relies on both the availability of brokers and non-brokers through October 2007 and the loss of brokers beginning in November 2007. OUS helped us to match administrative data on ORP participants with retirement account-level data from HIGH, LOW, and NEW.[6] Our account-level data end in December 2009.

The availability of HIGH until October 2007 allows us to study the demand for brokers

[4] See Chalmers, Johnson, and Reuter (2014) for a description of Oregon's Public Employees Retirement System.

[5] 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.

[6] As we show in Table 1, between October 1996 and October 2006, 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 SMALL and SMALLER because these providers were dropped from ORP on November 2007, which predates our data collection.

within a defined contribution retirement plan. When we focus on demographic characteristics, we find that demand for HIGH is negatively correlated with age, salary, and educational attainment. Demand for HIGH is also significantly lower among participants working in an economics department or business school. These patterns reinforce our prior that ORP participants are more likely to seek broker recommendations when they have lower levels of financial literacy or less investment experience. To provide more direct evidence on the demand for broker recommendations, we administered an online survey to current ORP participants, asking them to weight the factors that led them to choose their initial ORP provider. We find strong evidence that demand for HIGH is driven by demand for face-to-face help with asset allocation decisions. These findings imply that the portfolios of broker clients reflect the recommendations of their brokers, but they also raise serious questions about the portfolios that these clients would have held in the absence of any recommendations.

The removal of HIGH from the provider menu for participants joining ORP after October 2007 allows us to study the extent to which different default investment options are substitutes for brokers. Using account-level data from HIGH, LOW, and NEW, we identify participants who, after six months, are still allocating 100% of their retirement contribution to the default investment option. Between October 1996 and October 2006, demand for default investment options is low. It ranges from 2.9% for HIGH, where the default is a fixed annuity, to 9.5% for LOW, where it is a money market fund. Between November 2007 and December 2009, when new participants lack access to brokers, demand for default investment options increase significantly. It is 21.5% for LOW, where the default is still a money market fund, and 64.0% for NEW, where the default is a target-date fund (TDF). To provide more direct evidence on substitution, we show that the model used to predict demand for HIGH in the earlier period successfully predicts demand for the default investment option in the later period.[7] This is especially true when we focus on the set of participants who invest through NEW, suggesting that TDFs, which make asset allocation decisions for investors, are much closer substitutes for brokers than are money market funds.

Next, we estimate the causal effect of broker recommendations by comparing the actual portfolios of broker clients to counterfactual portfolios based on Fidelity TDFs. We find that

[7] Our approach both here and below is related to that in Calvet, Campbell, and Sodini (2009), who combine financial wealth, family size, and educational attainment into a financial 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.

broker clients earned significantly lower after-fee returns, lower risk-adjusted returns, and lower Sharpe ratios than they would have earned if they had been defaulted into age-specific Fidelity target-date funds.[8] A significant portion of the underperformance is due to broker fees, which average 90 basis points per year. Point estimates suggest that broker client portfolios are slightly riskier than the counterfactual TDF portfolios, but the differences are not statistically significant at conventional levels.[9]

Gennaioli et al. (2015) motivates another comparison of portfolio risk and returns. Their key prediction, based on the assumption that brokers reduce the disutility associated with bearing financial risk, is that actual portfolios of broker clients will hold more equity than counterfactual portfolios constructed without access to brokers. To test this prediction, we interact the predicted probability that a participant chooses to invest through HIGH with dummy variables indicating whether the participant does or does not invest through HIGH. To the extent that participants who are more comfortable bearing market risk are less likely to invest through a broker, our test will underestimate the impact of brokers on risk taking. Despite this potential bias, the estimated differences in risk taking are striking. Participants who are predicted to invest through a broker and do so hold portfolios with higher total risk (the volatility of monthly return is 1 percentage point higher) and higher systematic risk (the CAPM beta is 0.27 higher) than participants who are predicted to invest through a broker and do not.

We conclude our analysis by studying fund selection. When we exploit across-fund variation in the level of broker fees, we find that funds paying higher broker fees receive significantly higher contributions from broker clients. This complements the finding in Christoffersen et al. (2013) that broker fees influence fund-level flows. It also increases our confidence that HIGH investors rely on broker recommendations when deciding how to allocate their retirement contributions across funds. When we shift our focus from fees to lagged returns, we find evidence of return chasing by both broker clients and self-directed investors, at least with respect to the initial set of fund choices.

Our paper contributes to the literature on financial advice in two ways. First, we show

[8] As Balduzzi and Reuter (2014) document, Fidelity had the largest share of the market for TDFs at the beginning of our sample period, 1999.

[9] When we apply the same empirical strategy to self-directed investors, we find that actual portfolio risk is significantly lower than it would have been if self-directed investors had invested in TDFs. These differences partially reflect the finding above that approximately 10% of LOW portfolios remain invested in the default money market fund. Point estimates suggest that self-directed investors underperformed TDFs by economically significant margins, but the differences are not statistically significant at conventional levels.

that demand for broker recommendations within a defined contribution retirement plan is driven by demand for advice on asset allocation and fund selection. This is not surprising, since the scope for broker recommendations within ORP is limited to asset allocation and fund selection, but it raises the possibility that TDFs are effective substitutes for broker recommendations. Had we been studying demand for recommendations related to taxable investment strategies or estate planning, for example, we likely would have found positive correlations with income, age, and educational attainment, and we would have needed a different strategy to identify investors' counterfactual choices. Second, we provide direct evidence that TDFs are effective substitutes for brokers. Our evidence strengthens Mitchell and Utkus' (2012) interpretation that demand for TDFs in 401(k) plans reflects an implicit demand for financial advice. More importantly, it allows us to benchmark the portfolios of broker clients against counterfactual portfolios based on TDFs. Doing so reveals that broker clients' portfolios offer similar exposure to market risk, but earn significantly lower after-fee returns and Sharpe ratios. When we compare investors who do and do not use brokers during the first part of our sample period, we find differences in risk taking that are broadly consistent with the prediction of Gennaioli et al. (2015). This suggests that broker recommendations may be needed to increase risk taking by investors operating outside of defined contribution retirement plans. Within defined contribution retirement plans, however, we find that plan participants can achieve similar exposure to market risk at lower cost through the choice of a TDF as the default investment option.

II. Empirical Framework and Literature Review

We use a simple empirical framework to highlight the challenges that arise when attempting to measure the causal effect of broker recommendations on their clients' portfolios. It also highlights how our paper differs from existing studies of financial advisors. We begin with the observation that investors potentially differ along two dimensions. The first is whether they seek broker recommendations on asset allocation and fund selection. The second is whether they receive and follow these recommendations. The four possible cases are illustrated in Figure 1. We classify investors who seek, receive, and follow recommendations as (Yes, Yes). These investors are broker clients and their portfolios reflect the recommendations of their brokers. We classify investors who seek but neither receives nor follows recommendations as (Yes, No). The portfolios of these reluctantly self-directed investors shed light on how broker clients would have invested in the absence of broker recommendations; the challenge is to identify these investors in

Figure 1: Framework for Advice

	Get Advice? Yes	Get Advice? No
Want Advice? Yes	**(Y, Y)** Advice wanted and followed	**(Y, N)** Broker client's counterfactual portfolio
Want Advice? No	**(N, Y)** Unsolicited advice	**(N, N)** Self-directed

real world data. We classify intentionally self-directed investors as (No, No). If intentionally self-directed investors have greater financial knowledge or investment experience than investors seeking broker recommendations, the portfolios of these self-directed investors will be poor proxies for the counterfactual portfolios of broker clients.[10]

Potential broker client *i* benefits from receiving and following recommendations when:

$$E[U_i\,(\text{Yes, Yes})] - E[U_i\,(\text{Yes, No})] > 0.$$

This difference in expected utilities depends on the quality of the recommendations that client *i* follows. Everything else equal, we expect that clients will benefit more from unbiased recommendations than from biased recommendations:

$$E[U_i\,(\text{Yes, Yes(Unbiased)})] - E[U_i\,(\text{Yes, Yes(Biased)})] > 0.$$

However, broker clients may rationally prefer biased recommendations to no recommendations:

$$E[U_i\,(\text{Yes, Yes(Biased)})] - E[U_i\,(\text{Yes, No})] > 0.$$

This is because the difference in expected utilities also depends on how client *i* would have invested in the absence of broker recommendations. The lower the expected utility associated with client *i*'s counterfactual portfolio, the more likely he is to benefit even from biased recommendations. For example, investors with lower levels of financial literacy may be both more likely to seek broker recommendations and more susceptible when investing on their own to the forms of strategic complexity described in Gabaix and Laibson (2006) and Carlin (2009). In addition, the lower the expected utility associated with client *i*'s counterfactual portfolio, the more biased or

[10] 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.

expensive may be the recommendation that the client receives. For example, the fees charged by brokers in Gennaioli et al.'s (2015) model are higher when the expected benefits of broker services to their clients are larger precisely because there are larger gains from trade.

Rather than attempt to test for differences in expected utility, empirical studies of financial advisors test for differences in portfolio characteristics correlated with expected utility. The causal effect of broker recommendations on client portfolio characteristic Z is given by:

$$E[Z|(Yes, Yes)] - E[Z|(Yes, No)].$$

We can estimate the first term using data on the returns, risk exposures, and fees of the actual portfolios of broker clients, but the second term depends on the characteristics of the portfolios that broker clients would have held in the absence of broker recommendations.

The existing literature focuses on the quality of broker recommendations.[11] One branch analyzes fund-level data. Bergstresser, Chalmers, and Tufano (2009) show that broker-sold mutual funds underperform direct-sold mutual funds even after adding back the 12b-1 fees used to pay brokers. Del Guercio and Reuter (2014) rationalize this underperformance by showing that flows into broker-sold funds chase raw rather than risk-adjusted returns. They show that the underperformance of actively managed funds is limited to the broker-sold segment, where demand for index funds is extremely low. Christoffersen et al. (2013) show that flows into broker-sold funds are higher when funds pay higher fees to brokers. These papers reveal that broker-sold funds are lower quality than direct-sold funds, and they imply that broker recommendations are conflicted, but they do not shed light on how broker clients would have invested in the absence of brokers.

The other branch of the literature analyzes account-level data, often obtained from banks located outside the United States. Hackethal, Haliassos, and Jappelli (2012) and Karabulut (2013) use German data to show that broker clients underperform self-directed investors. These comparisons only measures the causal effect of brokers under the strong assumption that broker clients' portfolios would have resembled self-directed investor portfolios in the absence of recommendations Hackethal, Inderst, and Meyer (2012) also use portfolio-level data from a Ger-

[11] An interesting exception is Bhattacharya et al. (2012), who use an experimental design to estimate the causal effect of offering unbiased recommendations to investors who are not actively seeking them. In our framework, this corresponds to estimating: $E[Z|\{No, Yes(Unbiased)\}] - E[Y|\{No, No\}]$. They find that self-directed investors who choose to receive and follow the recommendations are able to improve their portfolios, but that demand for unsolicited recommendations is low. This is consistent both with the psychology literature on unsolicited advice described in Hung and Yoong (2013) and with their experimental evidence.

man bank to study trades by broker clients. They find that the bank earns higher revenues from the subset of clients who self-report placing the most trust in their brokers. Hoechle, Ruenzi, Schaub, and Schmid (2013) compare broker-initiated trades with self-initiated trades at a Swiss bank and find that broker-initiated trades underperform. Foerster, Linnainmaa, Melzer and Previtero (2014) find strong evidence that clients of financial advisors in Canada follow their recommendations but little evidence that advisors offer different advice to different clients. Finally, Mullainathan, Nöth, and Schoar (2012) use an audit study methodology to measure how recommended portfolios differ from the initial portfolios that the auditors show to brokers. They find strong evidence that broker recommendations are biased in directions that are likely to benefit brokers and little evidence that broker recommendations improve upon the initial portfolios.

These papers raise important questions about whether and how broker recommendations can be improved, but they are silent on how broker clients would have invested in the absence of these recommendations. In this paper, we use time-series variation in the access to brokers to show that TDFs are reasonable counterfactual portfolios for those investors most likely to seek investment advice inside a defined contribution retirement plan.

III. Who Seeks Broker Recommendations?

A. Institutional Details

In October 1996, the Oregon University System (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). OUS covers seven campuses and the Office of the Chancellor. When ORP was introduced, existing OUS employees had to make a "one-time, irrevocable" choice between ORP and PERS.[12] New OUS faculty, administrators, and other employees had to choose between ORP and PERS six months after they are hired, with the default option being PERS.

We study the sample of OUS employees who actively choose ORP over PERS.[13] We begin by exploiting the fact that, unlike a typical defined contribution plan, ORP participants are allowed to choose from among multiple investment providers. Between October 1996 and Octo-

[12] 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.

[13] Chalmers, Johnson, and Reuter (2014) study the retirement timing decisions of Oregon public employees who are covered by PERS and were never eligible for ORP. Chalmers and Reuter (2012) studies the demand by PERS retirees for life annuities versus lump sums.

ber 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.[14] It is important to note that the ORP retirement contribution amount both is set by OUS and paid by OUS on behalf of the employee. There is no scope for brokers to increase savings rates within ORP.[15] As a result, broker recommendations in our setting are limited to asset allocation and fund selection. This fact is likely to explain why we find that demand for financial advice is negatively correlated with proxies for financial literacy (like salary and educational attainment) while surveys and papers studying demand for financial advice in other settings find that it is positively correlated.

To identify how broker clients would have invested in the absence of broker recommendations, we exploit time-series variation in the set of investment providers available to new ORP participants. Effective November 2007, ORP drops HIGH, SMALL, and SMALLER, and adds NEW, a well-known mutual fund family.[16] The crucial change for our study is that ORP participants who join after October 2007 cannot choose to invest their retirement contributions through a broker.

We use administrative data from OUS to identify the provider through which each ORP participant chooses to invest. We report these counts in Table 1.[17] Between October 1996 and October 2007, LOW is the most popular provider. It is chosen by 50.7% of the 5,807 participants who join ORP during "Regime 1." HIGH, which offers face-to-face interactions with brokers, is also quite popular, and is chosen by 31.7% of participants. During "Regime 2," the period beginning in November 2007 and ending in December 2009, when our administrative data

[14] LOW eventually begin offering investors the opportunity to meet one-on-one with representative, who would provide participants with investment guidance, but not until 2006.

[15] Using OUS data we examined the use of supplementary 403(b) retirement plans by ORP participants. We found that approximately two percent of ORP participants who invest through HIGH open a 403(b) plan versus approximately one percent of all other ORP participants.

[16] Participants already investing through HIGH and LOW are allowed to continue doing so, while participants already investing through SMALL or SMALLER have their investments mapped into comparable funds managed by NEW.

[17] 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.

end, new participants are limited to LOW or NEW. Of the 734 participants who join during Regime 2, 54.8% choose LOW and 45.2% choose NEW.

The last two columns of Table 1 report the number of ORP-eligible employees who choose the defined contribution retirement plan, ORP, over the defined benefit retirement plan, PERS. During Regime 1, 24.3% of ORP-eligible employees choose ORP. During Regime 2, the fraction falls to 21.0%. This decline is smaller than we expected given our prior that the lack of access to brokers combined with negative equity market returns would increase the relative attractiveness of a retirement plan that manages assets on the employee's behalf (Brown and Weisbenner (2007)).

B. Participant Characteristics and the Choice of Investment Provider

Investors may seek broker recommendations because they lack the financial knowledge and confidence required to allocate retirement contributions across asset classes and funds, because they 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 employees of the Oregon University System, 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 important to keep this caveat in mind. The other important caveat is that we are studying the subset of employees who choose a defined contribution plan over a defined benefit plan.

Table 2 reports separate summary statistics for OUS employees who join ORP during Regime 1 and Regime 2. The sample sizes are lower than in Table 1 because we require data on each participant's initial monthly salary, gender, age, job classification, and self-reported ethnicity. The main comparison of interest in Table 2 is between participants who choose to invest through HIGH during Regime 1 (column (2)) and those who choose to invest through LOW, SMALL, or SMALLER (column (3)). This comparison allows us to determine which demographic characteristics are correlated with demand for broker recommendations within our sample of investors. Because we only possess account-level data for HIGH and LOW, column (4) reports statistics for participants who choose LOW, allowing a direct comparison between HIGH and LOW. We use job classification code to identify research faculty (i.e., job classification includes the string "Teach/Res"), participants who are employed by a business school or economics department, and participants who are employed by another "quantitative department" (i.e., organizational description includes a reference to business, computer sciences, engineering, life sciences, mathematics, physical sciences, or social sciences). We only possess data on educational attainment at the time of employment for 57.6% of ORP participants, because these data were only collected by a subset of campuses and only through December 2004.

Univariate comparisons between HIGH and the other providers (or LOW) reveal interesting differences. First, HIGH participants earn 14.1% lower monthly salaries than other participants who join ORP during Regime 1. Second, demand for HIGH is substantially higher in the under-30 age group (21.2% versus 15.6%), which likely includes participants with both the longest investment horizons and the least investment experience. Third, demand for HIGH decreases with educational attainment. Of those choosing HIGH, 39.7% have a Ph.D. versus 52.8% of those choosing to invest through other providers. These three differences suggest that—even within our relatively homogenous sample of faculty and administrators—demand for brokers falls with income, age, and education.[18] Consistent with studies that find lower levels of financial literacy among females and minorities (e.g., Lusardi and Mitchell (2007b) and Lusardi and Tufano (2009)), we also find higher demand for brokers among female participants. However, we find little evidence that demand for brokers varies with ethnicity.

Table 2 also allows us to compare the characteristics of employees who choose ORP during each sample period. In an ideal experiment, the 4,680 participants in Regime 1 would closely resemble the 614 participants in Regime 2. A comparison of columns (1) and (5), however, reveals several differences. Participants joining during Regime 2 have higher (nominal) salaries, are much more likely to be female, are younger, and are much less likely to be faculty members. To control for changes in participant composition across sample periods, we include all of these characteristics in the model that we use to predict demand for brokers. Because we lack data on educational attainment for the participants in Regime 2, however, we cannot directly control for any differences in education.

C. Predicting Demand for Broker Recommendations

We estimate a series of probits to identify those investor characteristics that predict demand for broker recommendations. The dependent variable in Table 3 is one if participant *i*'s initial ORP retirement contribution is directed to HIGH and zero otherwise. Column (1) of Table

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

3 reports coefficients estimated on the full sample of ORP participants described in Column (1) of Table 2. This sample includes participants for whom we do not observe the date of the choice (because all choices made before February 1999 are coded as January 1999), and it includes participants for whom we do not observe educational attainment. In Columns (2) and (3) of Table 3, we restrict the sample to participants for whom we observe the actual date of the initial ORP contribution. This restriction allows us to compare specifications that do and do not include a separate fixed effect for the year and month of the choice. The fixed effects allow us to control for time-varying economic conditions. In Columns (4) and (5), we further restrict our sample to those campuses and years for which data on educational attainment are available. We report marginal effects, along with standard errors clustered on the year and month of the choice.[19]

The marginal effects in Table 3 are largely consistent with the univariate comparisons. Given the fact that one-third of ORP participants choose to invest through HIGH, they are also economically significant. Increasing an employee's monthly salary by one standard deviation reduces demand for a broker by approximately seven percentage points. Similarly, employees who are less than 30 years old when hired (the omitted category) are approximately seven percentage points more likely to invest through a broker. Participants with PhDs are approximately 11 percentage points less likely to invest through a broker, and those employed by a business school or economics department are between 9 and 17 percentage points less likely to invest through a broker. The one notable difference between Table 2 and Table 3 is that when we restrict the sample to those participants for which we observe data on educational attainment, we find female participants are approximately 5 percentage points less likely to invest through a broker. With respect to ethnicity, many of the estimated coefficients are positive and economically significant (relative to the omitted category "White"), but only the dummy variable indicating whether participant *i* reports being Asian is statistically significant. When we control for variation in market conditions by including a separate fixed effect for the year and month of the choice, the estimated coefficients on participant characteristics are quantitatively similar to those obtained in specifications that do not include the fixed effects.

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 one of the three regional campuses than at University of Oregon (the omitted category). The lower demand for

[19] Since choices made before February 1999 are coded as January 1999, and these choices are included in the sample used to estimate coefficients in Column (1), in this sample, we allow for clustering in all of the early choices.

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 regional campuses—is that across-campus differences in demand for HIGH reflect variation in the quality or accessibility of the broker(s) assigned to each campus.

Overall, our evidence on which participants choose HIGH 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. The lower demand for brokers by employees of business schools and economics departments lends further support to this interpretation. In the next section, we use survey evidence to shed additional light on the demand for broker recommendations. In later sections, we use the predicted values from the probits estimated in Table 3 to predict demand for default investment options and to explain variation in portfolio risk taking and returns.

D. Survey Evidence on the Demand for Broker Recommendations

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 existing plan design and to solicit feedback on several potential changes, we were permitted to add several questions related to the use of brokers, financial literacy, and risk aversion. Of the 1,380 (38%) completed survey responses, 990 are from ORP participants who chose either HIGH (313) or one of the other providers (690) during Regime 1. The survey responses for these investors provide us with another opportunity to determine why some investors choose to invest through a broker and others do not. The limitation is that we are using investors' attitudes and traits measured in 2012 to assess choices made as far back as October 1996.

Table 4 Panel A reinforces the idea that investors choose HIGH when they lack the confidence to invest on their own. Investors who originally chose HIGH are significantly more likely to have "an ongoing 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 39.8%; p-value of 0.000). Moreover, when asked how they primarily decided on 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 45.1%; p-value of 0.000).

Panel B reveals that 85.0% of the investors who still invest through HIGH meet with their broker at least once a year. It also reveals that those still investing through HIGH are more likely to implement advice quickly (43.4% versus 27.1%) and less likely to ignore advice (8.2% versus 15.2%) than other investors. Interestingly, only 23.1% 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 investors invest through brokers because they value their investment advice. It also reveals that HIGH investors seek "peace of mind" from an advisor that they can trust, lending support to a key assumption in Gennaioli et al. (2015).

Panel D describes the weights that ORP participants place on four provider characteristics: "Access to face-to-face meetings with a financial adviser," "The number of equity fund choices available," "The level of fund expenses," and "Historical investment performance." Consistent with earlier answers, we find that investors who chose HIGH are significantly more likely to rank access to face-to-face meetings as important or very important (69.9% versus 38.2%; p-value of 0.000). The fact that HIGH provides access to both broker recommendations and a larger menu of investment options raises the possibility that demand for HIGH is also driven by demand for the larger menu. 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.) We find that slightly fewer 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), but the difference is neither economically large nor statistically significant. The fact that HIGH investors claim to place slightly less weight on historical fund returns when choosing between providers (80.8% versus 87.2%; p-value of 0.011) is interesting in light of our findings in section V.B. that HIGH investors appear more likely to chase lagged returns when initially 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 the Health and Retirement Survey (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 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 92.8% of LOW investors. While the 2.8% difference is statistically significant at the 10-

percent level (p-value of 0.061), it is not economically large. In other words, to the extent that demand for investment recommendations is driven by variation in financial literacy, that variation is not well captured by answers to standard financial literacy questions. Finally, to measure risk aversion, we include 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%). Our finding that HIGH investors are less likely to prefer "Job 2" across all three scenarios suggests that they are more risk averse, on average, but none of the differences are statistically significant at conventional levels.

IV. Default Investments As Substitutes For Broker Recommendations?

The fact that demand for HIGH is driven by demand for recommendations on asset allocation and fund selection begs the question how would broker clients invest without their brokers' recommendations? We are able to answer this question in our setting, by exploiting OUS's decision to drop HIGH from the set of investment providers available to new participants in November 2007. We hypothesize that removing access to brokers recommendations from ORP will increase demand for default investment options *by those investors who would have otherwise chosen to invest through HIGH*. Because TDFs reduce their exposure to equity as the target retirement date draws near, they offer participants the opportunity to invest in a single fund that bundles asset allocation with portfolio management. Therefore, we further hypothesize that the substitution of default investment options for broker recommendations will be strongest when the default is a TDF.

With OUS's assistance, we obtained account-level data from HIGH, LOW, and NEW. We describe these data in detail below, when we describe our measures of portfolio risk and returns. For now, the key feature of the account-level data is that they allow us to identify those participants who allocate 100% of their retirement contributions to their provider's default investment option. To allow for the possibility that it takes investors several months to actively choose their investments, for both HIGH and LOW, we focus on participant *i*'s contribution five months after his initial contribution. For NEW, which only provides us with data on quarterly account balances, we focus on participant *i*'s holdings at the end of the second quarter.

Table 5 summarizes demand for default investment options during Regime 1, when HIGH and LOW are available to new members, and Regime 2, when only LOW and NEW are available. Note that the default investment option differs across the three providers. For HIGH, it is a fixed annuity; for LOW, it is a money market fund; and for NEW, it is a TDF with the target retirement date chosen based on the participant's age.[20] Panel A focuses on the full sample of ORP participants, and Panel B focuses on the sample of participants for which we possess the administrative data required to estimate the model in Column (2) of Table 3 (regardless of whether the participant joined ORP during Regime 1 or Regime 2). The fraction of participants who demand the default option varies across the two samples of participants, but only slightly.

Table 5 reveals several interesting patterns. First, the fraction of participants that remain invested in the default increases sharply after HIGH is dropped from the set of providers, from less than 10% in Regime 1 to more than 40% in Regime 2. Second, during Regime 1, the fraction of broker clients that remain invested in the default option is less than 3%. Third, approximately 65% of the participants who choose to invest through NEW remain invested in the TDF. The strong demand for TDFs in Regime 2 is consistent with our hypothesis that TDFs are *de facto* substitutes for broker recommendations. Finally, demand for LOW's default investment option approximately doubles between Regime 1 and Regime 2. This may reflect the fact that some of the participants who previously would have chosen to invest through HIGH choose LOW but lack the confidence to allocate their retirement contributions to non-default investment options. Or, because Regime 2 includes the onset of the recent financial crisis, the increased demand for LOW's money market funds may reflect a conscious response to declining equity market values.

Table 6 provides direct evidence on the extent to which default investments are substitutes for broker recommendations. In the spirit of Calvet, Campbell, and Sodini (2009), we use the estimated coefficients in Column (2) of Table 3 to predict demand for brokers and then regress demand for the default investment option on the predicted demand.[21] We include a separate fixed effect for the year and month of the choice, to control for average changes in the demand for defaults based on changes in market conditions, and we cluster standard errors on this date. We find that demand for the default during Regime 1 is unrelated to predicted demand for brokers. This likely reflects the fact that investors who are the least confident picking their own funds self-select into HIGH, where brokers then actively recommend other investments. On the

[20] OUS' decision to limit the set of providers in 2007 was a response to the Pension Protection Act of 2006, which effectively encouraged firms to offer TDFs as default investment options (Balduzzi and Reuter (2013)).

[21] Findings are similar when we use predicted values from Column (1), which allows us to include participants for whom the date of the choice is not observed, but prevents us from include a fixed effect for the date of the choice.

other hand, during Regime 2, when brokers are no longer available during Regime 2, we find that demand for defaults is strongly related to predicted demand for brokers.

Pooling participants who choose LOW or NEW, we find that investors whose predicted values are in the top quartile are 19.2 percentage points more likely to demand the default investment option than investors whose predicted values are in the bottom quartile, a difference that is statistically significant at the 1-percent level. However, because this specification treats demand for LOW's default money market fund the same as demand for NEW's default TDF, it masks significant differences across the two providers. When we limit our sample to participants who choose to invest through NEW, we find an even stronger positive relation between demand for the default and predicted demand for brokers. The coefficient on Pr(HIGH) increases from 0.536 to 0.764. Demand for TDFs by investors in the top quartile of predicted demand for brokers is 27.5 percentage points higher than by investors in the bottom quartile, and the difference remains statistically significant at the 1-percent level. However, when we limit the sample to participants who choose to invest through LOW, we find that predicted demand for brokers does not help to predict demand for the default money market fund. This suggests that the increased demand for the money market fund during Regime 2 is driven by different factors than the increased demand for TDFs.

Mitchell and Utkus (2012) study fund selection in a large number of 401(k) plans that do not offer access to brokers and conclude that demand for TDFs reflects an underlying demand for investment advice. Our findings strengthen their conclusion. More importantly, because we find many potential broker clients invest 100% of their retirement contributions in TDFs when brokers are not available, in the next section we are able to use counterfactual portfolios based on TDFs to measure the causal impact of broker recommendations on their clients' portfolios.

V. Causal Effect of Broker Recommendations on Broker Client Portfolios

A. Testing for Differences in Risk and Return

To measure the causal impact of broker recommendations on their client portfolios we require data on both the actual and counterfactual portfolios of ORP participants who choose to invest through HIGH. To test the risk-taking hypothesis of Gennaioli et al. (2015), we require data on the actual portfolios of ORP participants who choose to invest through LOW.

We combine the participant-level administrative 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 options. 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 option. 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 notably, it leads us to focus on differences in annual after-fee returns.

To calculate the actual 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 six-factor model that adds the excess return on the MSCI Barra EAFE index, to capture exposure to international equity, and the excess return on the Barclay U.S. Aggregate Bond index, to capture exposure to fixed income. To calculate risk-adjusted returns for participant *i* in year *t*, we subtract 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*. To calculate the volatility of monthly returns, we use account balances at the beginning of year *t* and monthly investment returns to calculate changes in monthly account balances during year *t*.

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 (2013)), 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 pick the single TDF with the closest target retirement date.[22] We then use monthly fund-level data from Fidelity to calculate annual risk-adjusted returns and the volatility of monthly returns. Because allocations to TDFs are determined entirely by investor age, variation in counterfactual portfolios across HIGH (and LOW) investors is driven by variation in the distribution of investor ages.

Table 7 compares actual investor portfolios to counterfactual portfolios based on TDFs. Panel A reveals that broker clients earned annual after-fee returns during our sample period that were 2.98% lower than they would have earned investing in TDFs (1.85% versus 4.85%). Approximately one-third of this difference can be explained by the fact that TDFs are less expensive than brokers. Broker clients in ORP pay average annual broker fees of 0.90% on top of the management and administrative fees and charged by the underlying investments. Broker clients' portfolios also exhibit more risk taking than the counterfactual portfolios, with larger differences when we focus on the volatility of monthly returns (3.81% versus 3.38%) than when we focus on CAPM beta (0.852 versus 0.796). The size of these differences varies over time, helping to explain the difference in returns. Specifically, the counterfactual portfolios benefit from 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. As a result, the average annual after-fee return earned by TDFs exceeded the average annual after-fee return earned by actual broker client portfolios in nine of the eleven years. Expressed as a fraction of investor-year observations, TDFs outperform actual broker client portfolios 71.0% of the time. These comparisons imply that brokers significantly increased annual fees, significantly decreased annual after-fee returns, and slightly increased risk taking relative to the counterfactual portfolios.

Panel B reveals that self-directed investor earn lower annual after-fee returns than TDFs, but the level of underperformance is 1.73% per year instead of 2.98% per year. Expressed as a fraction of investor-year observations, TDFs outperform self-directed investors 61.1% of the time. However, self-directed investors also bear less risk. The average CAPM beta of their actual portfolios is 0.601 (versus 0.817 for TDFs) and the average volatility of monthly returns is

[22] In earlier drafts, we assigned 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 was 2029, we allocated 10% of the portfolio to the Fidelity Freedom 2020 fund and 90% to the Fidelity Freedom 2030 fund. Our findings were quantitatively similar.

2.56% (versus 3.50%). Some of the lower average risk taking is due to the fact that approximately 10% of self-directed investors remain invested in the money market fund, which is the default investment option. Although we might expect some self-directed investors to replace their actual portfolios with TDFs following the introduction of TDFs to ORP, the comparisons in Panel B lack any sort of causal interpretation.

It follows from the comparisons above that broker clients underperform self-directed investors by 1.28% per year. This is partially due to the average annual fees of 0.90% that broker clients pay to their brokers. However, the 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 reinforce the conclusion that broker clients bear significantly more risk than self-directed investors. One interpretation is that brokers recommend greater-than-optimal levels of risk, perhaps because more volatile returns make it harder for their clients to detect underperformance. In terms of the average level of systematic risk, however, broker client portfolios resemble TDF portfolios. Another interpretation, in the spirit of Gennaioli et al. (2015), is that self-directed investors hold lower-than-optimal levels of risk. We explore this possibility in Table 8.

In Panel A, we test for differences in the characteristics of actual and counterfactual portfolios. The set of characteristics is expanded to include six-factor alphas and Sharpe ratios. The odd-numbered columns are limited to the sample of broker clients and the even-numbered columns are limited to the sample of self-directed investors. In each case, we regress the characteristic of participant *i*'s actual portfolio minus the characteristic of his counterfactual portfolio on a constant, which captures the average difference. To allow for correlations both in annual portfolio returns across participants in year *t* and in participant *i*'s annual portfolio returns across years, we cluster standard errors on year t and participant *i*. The patterns are broadly consistent with the patterns in Table 7. Namely, broker clients earn lower annual after-free returns (-3.21%; statistically significant at the 1-percent level), lower annual risk-adjusted, after-fee returns (-2.11%; 5-percent level), and lower Sharpe ratios (-0.1436; 5-percent level).[23] But, we cannot reject the

[23] In Panel A, the Sharpe ratio is defined as the average difference in monthly returns of the actual and counterfactual portfolios, scaled by the standard deviation of the difference in monthly returns. In Panel B, the Sharpe ratio is

hypothesis that the actual and counterfactual portfolios have the same levels of systematic and total risk. This leads us to conclude that TDFs are just as effective as brokers in helping investors increase portfolio risk.

In Panel B, we use a different empirical strategy to estimate the causal impact of broker recommendations. The odd-numbered columns test for differences between the actual portfolios of broker clients to the actual portfolios of self-directed investor, including a separate fixed effect for each calendar year. While the point estimates suggest that broker clients underperform by economically significant amounts, none of the performance differences is statistically significant. In contrast, the estimated differences in risk taking are both economically and statistically significant.

The even-numbered columns are more interesting because they allow us to compare the portfolios of broker clients and self-directed investors who are both predicted to invest through HIGH. 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. Again, 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 systematically different portfolios relative to 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. Because portfolio returns will be highly correlated across participants investing during the same year, standard errors are also clustered on calendar year.

We find that predicted demand for brokers has opposite effects on risk taking in the two samples of investors. 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 0.177 *but* decrease the CAPM beta of self-directed investors by 0.112—a economically and statistically significant

defined as the average monthly return of the actual portfolio minus the risk-free rate of return, scaled by the standard deviation of the excess monthly return.

difference of 0.289. When we shift our focus to the volatility of monthly returns, in column (4), the findings are qualitatively similar. Higher predicted values are associated with greater volatility when the participant invests through HIGH and lower volatility when he does not. In unreported regressions, we restrict the sample to investors who answer the survey question about the value they place on face-to-face meetings, scale the answer to range between 0 ("unimportant") and 1 ("very important"), and estimate a version of Table 8 with interaction terms based on this measure instead of PR(HIGH). We find that plan participants who place greater value on face-to-face advice but invest through LOW have significantly less volatile portfolio returns and significantly lower CAPM betas than similar plan participants who invest through HIGH. The differences in Table 8 and the unreported regressions are consistent with brokers tilting their clients toward riskier investments to more readily mask underperformance, but also with Gennaioli et al.'s (2015) assumption that brokers reduce the disutility associated with bearing financial risk. Nevertheless, our findings in Panel A suggest that TDFs are a more cost-effective way to increase risk-taking by less experienced investors.

B. Comparing the Investment Selection of HIGH and LOW Investors

To implement an asset allocation plan, an investor must allocate her monthly retirement contributions across an appropriate set of funds. In Table 9, we explore the impact of brokers on fund selection. We test two hypotheses. The first concerns the agency conflict that can arise when financially unsophisticated (or trusting) investors seek investment recommendations from financially sophisticated intermediaries. To test for conflicted advice, we exploit 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. Here, our research question most closely matches that of Christoffersen et al. (2013), who find that cross-sectional variation in the level of broker fees helps to explain cross-sectional variation in mutual fund flows, and Hackethal, Inderst, and Meyer (2012), who find that broker recommendations respond to sales incentives.

The second hypothesis concerns return chasing. Within the full universe of mutual funds, there is strong evidence that the relation between flows and performance is convex, with the best performing mutual funds receiving a disproportionate share of the dollars.[24] At the same time, because studies like Carhart (1997) find little evidence that abnormal returns persist, investors

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

should not make long-term asset allocation decisions on recent fund-level returns. Therefore, we test whether return-chasing behavior differs between broker clients and self-directed investors. To the extent that brokers discourage return chasing, we expect to find less evidence of return chasing by broker clients. The implicit assumption underlying this comparison is that broker clients would have been at least as likely to engage in return chasing without a broker. An alternative test is whether broker clients' exhibit any return chasing at all since there can be no return chasing in a portfolio that allocates 100% to a single TDF.

The dependent variable in Table 9 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 of the funds available to HIGH or LOW investors in month *t*. To focus attention on active fund choices, we exclude those participants who invest solely in the default option. There are three independent variables of interest. To test for conflicted advice, 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, it 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 the "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. 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.

One set of specifications focus on initial fund choices (month 1) and another set focus on choices (month 24). All of our specifications control for the fund's broad asset category, turnover, and whether it is an index fund. Because we are testing for differential sensitivities to lagged returns and fees across ORP providers, in columns (1) and (4), we 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. In the other columns, we include a separate fixed effect for each provider-asset category-month combination, so that we are comparing fund returns and fees within a given menu and category. When we focus on narrow categories instead of broad categories (e.g., small-cap value funds instead of domestic equity funds), we limit the sample to HIGH equity funds. Standard errors are clustered on date.

We find strong evidence of conflicted investment recommendations. The coefficients on the level of broker fees are positive and statistically significant in all six columns, and the magnitudes are economically significant. Increasing broker fees by 50 basis points (i.e., the difference between the lowest and highest broker fee) is predicted to increase the allocation to investment j by as much as 35.3 percentage points. 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. 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.

The evidence on return chasing is mixed. HIGH investors consider recent returns when selecting funds in month 1, but not in month 24. Therefore, to the extent that brokers help investors chase past returns, they only do so when initially selecting funds. However, the effects in month 1 are economically significant. A one-standard deviation increase in recent returns is predicted to increase the allocation to investment j by 10.6 percentage points. Whether we find that LOW investors consider recent returns depends on the specification. The baseline specifications suggest no return chasing in month 1 but modest return chasing in month 24. The specifications that include provider-broad asset class-month fixed effects suggest strong return chasing in months 1 and 24. The caveat is that because the LOW menu tends to offer a single fund within each broad asset class, the estimated coefficient is driven by allocations to the three equity funds.

IV. Conclusion

While there is growing evidence that broker recommendations are conflicted, the net benefit of broker recommendations depends on the quality of the recommendations and the quality of the client's counterfactual portfolio. We use unique investor-level data from the Oregon University System to estimate the causal impact of brokers on their clients' retirement portfolios. We have four main findings.

First, we document significant differences between those investors who choose to invest through brokers and those 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. These differences beg the question of how broker clients would have invested in the absence of broker recommendations. For example, the fact that many retirement plans historically tended not to offer one-on-one advice may help to explain why Tang, Mitchell, Mottola and Utkus (2010) find that 401(k) plan participants presented with well-designed investment menus still tend to hold inefficient retirement portfolios.

Second, we use time-series variation in access to brokers to identify the counterfactual portfolios of would-be broker clients. We show that demand for default investment options more than quadruples after HIGH is dropped from the set of providers. More importantly, we show that the model used to predict demand for brokers when HIGH is a choice successfully predicts demand for Fidelity's TDF default investment option when HIGH is not a choice. Mitchell and Utkus (2012) find that TDFs are popular with younger, lower income investors, and argue that this popularity follows from the fact that TDFs offer both portfolio management and asset allocation. In our setting, where investment recommendations are limited to asset allocation and fund selection, we document that TDFs are *de facto* substitutes for broker recommendations.

Third, we provide new evidence on conflicted advice. Our account-level finding that brokers are significantly more likely to place their clients in funds that pays larger broker fee complements the fund-level finding in Christoffersen, et al. (2013).

Fourth, when we benchmark broker client portfolios against counterfactual portfolios based on TDFs, we find that broker recommendations lead to higher annual fees (due in part to average annual broker fees of 0.90%), lower risk-adjusted returns, and lower Sharpe ratios, but similar levels of exposure to market risk. In other words, within the context of a retirement plan that offers a default investment option, choosing a reasonable TDFs as the default can decrease annual fees without decreasing risk taking. On the other hand, when we compare the outcomes of investors with high predicted demand for broker recommendations during Regime 1 (before TDFs are available), we find that broker clients have much higher levels of exposure to market risk. These findings, which are consistent with Gennaioli et al. (2015), highlight the possibility that brokers may add more value in settings that lack a sensible default option.

Although our estimates come from a single DC retirement plan, in this study we are able to uniquely identify the impact of brokers relative to an implementable counterfactual. This allows us to directly address the self-selection by investors to be broker advised versus self-directed. In other words, we are able to overcome a problem that has plagued inferences of causality in the literature that asks: what is the value of advice? This is a crucial economic issue because DC retirement plans place important investment decisions in the hands of individuals, many of whom possess limited financial knowledge (e.g., Lusardi and Mitchell (2006)). Choi, Laibson and Madrian (2004) demonstrate that automatic enrollment had a huge impact on 401(k) participation rates thus improving savings rates. We demonstrate that a well-chosen default investment option dominates access to broker recommendations and provides improved risk taking and stock market participation in retirement portfolios. To the extent that investors derive utility from face-to-face meetings with brokers that they do not derive from TDFs, this utility needs to be weighed against the higher fees and likelihood of conflicted advice.

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.[25] 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.[26]

[25] 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.
[26] 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 managed 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, as we discuss above, the two providers have different default investments. The default in LOW is a money market, while the default in HIGH is a fixed annuity. However, it is an open question which if any of the differences in investment menus influenced the choice of ORP provider. In Table A2, we summarize the information about investment provider menus that OUS provided to new employees in 2002. This information understated the differences in the sizes of the investment menus.

References

Agnew, Julie, Pierluigi Balduzzi, and Annika. Sunden, 2003, "Portfolio Choice and Trading in a Large 401(k) Plan," *American Economic Review* 93, 193–205.

Anagol, Santosh, Shawn Cole, and Shayak Sarkar, 2013, "Understanding the Incentives of Commissions Motivated Agents: Theory and Evidence from the Indian Life Insurance Market," Harvard Business School Working Paper.

Balduzzi, Pierluigi, and Jonathan Reuter, 2013, "Heterogeneity in Target-Date Funds: Optimal Risk Taking or Risk Matching?" NBER Working Paper 17886.

Barber, Brad, and Terrance Odean, 2000, "Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," *Journal of Finance* 55, 773–806.

Barber, Brad, and Terrance Odean, 2001, "Boys Will be Boys: Gender, Overconfidence, and Common Stock Investment," *Quarterly Journal of Economics* 116, 261–292.

Barber, Brad, Terrance Odean, and Lu Zheng, 2005, "Out of Sight, Out of Mind: The Effects of Expenses on Mutual Fund Flows," *Journal of Business* 78, 2095–2120.

Bernheim, Douglas, Daniel Garrett, and Dean Maki, 2001, "Education and saving: The long-term effects of high school financial curriculum mandates," *Journal of Public Economics* 80, 435–465.

Bhattacharya, Utpal, Andreas Hackethal, Simon Kaesler, Benjamin Loos, and Steffen Meyer, 2012, "Is Unbiased Financial Advice to Retail Investors Sufficient? Answers from a Large Field Study," *Review of Financial Studies* 25, 975–1032.

Benartzi, Shlomo, 2001, "Excessive Extrapolation and the Allocation of 401(k) Accounts to Company Stock," *Journal of Finance* 56, 1747–1764.

Benartzi, Shlomo, and Richard Thaler, 2001, "Naive Diversification Strategies in Defined Contribution Saving Plans," *American Economic Review* 91, 79–98.

Bergstresser, Daniel, Chalmers, John, Tufano, Peter, 2009, "Assessing the Costs and Benefits of Brokers in the Mutual Fund Industry," *Review of Financial Studies* 22, 4129–4156.

Behrman, Jere, Olivia Mitchell, Cindy Soo, and David Bravo, 2010, "Financial Literacy, Schooling, and Wealth Accumulation," Pension Research Council Working Paper 2010-24.

Brown, Jeffrey, and Scott Weisbenner, 2007, "Who Chooses Defined Contribution Plans?" NBER Working Paper 12842.

Calcagno, Riccardo and Chiara Monticone, 2014, "Financial literacy and the demand for financial advice," forthcoming *Journal of Banking and Finance*.

Calvet, Laurent, John Campbell, and Paolo Sodini, 2009, "Measuring the Financial Sophistication of Households," *American Economic Review* 99, 393–398.

Campbell, John, 2006, Household Finance, Journal of Finance 61, 1553−1604.

Carhart, Mark, 1997, "On Persistence in Mutual Fund Performance," *Journal of Finance* 52, 57–82.

Carlin, Bruce, 2009, "Strategic Price Complexity in Retail Financial Markets," *Journal of Financial Economics* 91, 278–287.

Chalmers, John, Woodrow Johnson, and Jonathan Reuter, 2014, "The Effect of Pension Design on Employer Costs and Employee Retirement Choices: Evidence from Oregon," *Journal of Public Economics* 116, 17–34

Chalmers, John, and Jonathan Reuter, 2012, "How Do Retirees Value Life Annuities? Evidence from Public Employees," *Review of Financial Studies* 25(8), 2601−2634

Chevalier, Judith A., and Glenn Ellison, 1997, "Risk-Taking by Mutual Funds as a Response to Incentives," *Journal of Political Economy* 105, 1167–1200.

Choi, James J., David Laibson, Brigitte C. Madrian, 2004, Plan design and 401(k) Savings Outcomes, *National Tax Journal*, 57, 2, 275-298.

Choi, James J., David Laibson, Brigitte C. Madrian, 2011, $100 Bills on the sidewalk: suboptimal investment in 401(K) plans, *The Review of Economics and Statistics*, 93, 3, 748-763.

Christoffersen, Susan, Richard Evans, and David Musto, 2013, "What Do Consumers' Fund Flows Maximize? Evidence from Their Brokers' Incentives," *Journal of Finance* 68, 201–235.

Del Guercio, Diane, and Paula Tkac, 2002, "The Determinants of the Flow of Funds of Managed Portfolios: Mutual Funds versus Pension Funds," *Journal of Financial and Quantitative Analysis* 37, 523-557.

Del Guercio, Diane, Jonathan Reuter, and Paula Tkac, 2010, "Broker Incentives and Mutual Fund Market Segmentation," NBER Working Paper 16312.

Del Guercio, Diane, and Jonathan Reuter, 2014, "Mutual Fund Performance and the Incentive to Generate Alpha," *Journal of Finance* 69, 1673–1704.

Elton, Edwin J., Martin J. Gruber, and Jeffrey Busse, 2004, "Are Investors Rational? Choices Among Index Funds," *Journal of Finance* 59, 261–288.

Fama, Eugene, and James MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy* 81, 607–636.

Finke, Michael, 2013, "Financial Advice: Does it make a difference?," 229-248, in *The Market of Retirement Advice*, edited by, Olivia S. Mitchell and Kent Smetters, Oxford University Press, 2013.

Foerster, Stephen, Juhani Linnainmaa, Brian Melzer, Alessandro Previtero, 2014, "Retail Financial Advice: Does One Size Fit All?", NBER Working Paper 20712.

Gabaix, Xavier, and David Laibson, 2006, "Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets," *Quarterly Journal of Economics* 121, 505–540.

Gaudecker, Hans-Martin von, 2015, "How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice," *Journal of Finance*, forthcoming.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2015, "Money Doctors," *Journal of Finance* 70, 91–114.

Georgarakos, Dimitris, and Roman Inderst, 2011, "Financial Advice and Stock Market Participation," ECB Working Paper 1296.

Gruber, Martin J., 1996, "Another Puzzle: The Growth in Actively Managed Mutual Funds," *Journal of Finance* 51, 783–810.

Hackethal, Andreas, Michael Haliassos, Tullio Jappelli, 2012, Financial Advisors: A case of babysitters?, Journal of Banking and Finance, 36, 509-524.

Hastings, Justine, Olivia S. Mitchell, Eric Chyn, 2010, Fees, framing and financial literacy in the choice of pension manager, PRC WP2010-09, The Wharton School.

Hung, Angela A. and Joanne K. Yoong, 2013, "Asking for Help: Survey and Experiemental Evidence on Financial Advice and Behavior Change," 189-212, in *The Market of Retirement Advice*, edited by, Olivia S. Mitchell and Kent Smetters, Oxford University Press, 2013.

Inderst, Roman and Marco Ottaviani, 2012, "Financial Advice," *Journal of Economic Literature*, 50, 2, 494-512.

Ippolito, Richard A., 1992, "Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry," *Journal of Law and Economics* 35, 45–70.

Hackethal, Andreas, Michael Haliassos and Tullio Jappelli, 2012, "Financial Advisors: A case of babysitters?," Journal of Banking and Finance, 36, 509-524.

Hackethal, Andreas, Roman Inderst, and Steffen Meyer, 2011, "Trading on Advice," working paper.

Hoechle, Daniel, Stefan Ruenzi, Nic Schaub, Markus Schmid, 2013, "Don't answer the phone-Financial advice and individual Investors' performance," April 23, 2013 working paper.

Karabulut, Yigitcan, 2013, "Financial Advice: An Improvement for Worse?" Working Paper, June 17, 2013.

Lusardi, Annamaria and Olivia S. Mitchell, 2006, "Financial Literacy and Planning: Implications for Retirement Wellbeing," Working Paper.

Lusardi, Annamaria, and Olivia S. Mitchell, 2007a, “Baby Boomer Retirement Security: The Role of Planning, Financial Literacy, and Housing Wealth,” *Journal of Monetary Economics* 54, 205–224.

Lusardi, Annamaria, and Olivia Mitchell, 2007b, “Financial Literacy and Retirement Preparedness: Evidence and Implications for Financial Education Programs,” Working Paper.

Lusardi, Annamaria, and Peter Tufano, 2009, “Debt Literacy, Financial Experiences and Over-indebtedness,” NBER Working Paper 14808.

Madrian, Brigitte, and David Shea, 2001, The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior, *Quarterly Journal of Economics* 116, 1149–1187.

Mitchell, Olivia, and Stephen Utkus, 2012, “Target-Date Funds in 401(k) Retirement Plans,” NBER Working Paper 17911.

Mullainathan, Sendhil, Markus Nöth, and Antoinette Schoar, 2012, “The Market for Financial Advice: An Audit Study,” NBER Working Paper 17929.

Odean, Terrance, 1998, “Are Investors Reluctant to Realize Their Losses?,” *Journal of Finance* 53, 1775–1798.

Odean, Terrance, 1999, “Do Investors Trade Too Much?,” *American Economic Review* 89, 1279–1298.

Philippon, Thomas, 2013, Has the U.S. Finance Ind

Reuter, Jonathan, and Eric Zitzewitz, 2006, “Do Ads Influence Editors? Advertising and Bias in the Financial Media,” *Quarterly Journal of Economics* 119, 197–227.

Sirri, Erik, and Peter Tufano, 1998, “Costly Search and Mutual Fund Flows,” *Journal of Finance* 53, 1589–1622.

Tang, Ning, Olivia S. Mitchell, Gary R. Mottola, Stephen P. Utkus, 2010, The efficiency of sponsor and participant portfolio choices in 401(k) plans, *Journal of Public Economics*, 94, 1073-1085.

Xu, Lisa, and Bilal Zia, 2012, “Financial Literacy Around the World: An Overview of the Evidence with Practical Suggestions for the Way Forward,” Policy Research Working Paper 6107, The World Bank.

Table 1. Number of New ORP Participants by Provider, October 1996 - December 2009

Date Range	Observe Date of Choice?	HIGH	LOW	SMALL	SMALLER	NEW	ORP	PERS
Regime 1. HIGH is available to new ORP participants								
10/96 - 01/99	No	603	699	274	66		1,642	2,996
02/99 - 12/99	Yes	141	169	55	24		389	1,864
01/00 - 12/00	Yes	153	192	57	25		427	2,004
01/01 - 12/01	Yes	108	204	52	15		379	1,869
01/02 - 12/02	Yes	91	229	56	14		390	1,915
01/03 - 12/03	Yes	133	275	28	31		467	1,663
01/04 - 12/04	Yes	130	244	45	18		437	1,517
01/05 - 12/05	Yes	197	294	46	37		574	1,557
01/06 - 12/06	Yes	148	285	53	30		516	1,476
01/07 - 10/07	Yes	139	355	57	35		586	1,222
TOTAL		**1,843**	**2,946**	**723**	**295**		**5,807**	**18,083**
Regime 2. HIGH is not available to new ORP participants								
11/07 - 12/07	Yes		11			15	26	189
01/08 - 12/08	Yes		182			169	351	1,304
01/09 - 12/09	Yes		209			148	357	1,261
TOTAL			**402**			**332**	**734**	**2,754**

Note: We use Oregon University System payroll data to identify the provider to which new Optional Retirement Plan (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. Between October 1996 and October 2007, participants have the choice of four providers: SMALL, SMALLER, LOW, and HIGH. Only HIGH markets itself as providing personal face-to-face service. Because OUS payroll data begin in January 1999, initial contribution dates before February 1999 are left censored at January 1999. Between November 2007 and December 2009 (the end of our sample period), new ORP participants are limited to investing through LOW or NEW. The last two columns of the table report the number of OUS employees who self-select into ORP versus PERS, the defined benefit retirement plan.

Table 2. Participant Summary Statistics

Date Range:	Regime 1				Regime 2
ORP Participants who choose:	Any Provider	HIGH	Not HIGH	LOW	Any Provider
	(1)	(2)	(3)	(4)	(5)
Sample Size	4,680	1,544	3,136	2,314	614
Monthly Salary (mean)	\$4,291	\$3,844	\$4,511	\$4,666	\$5,235
Monthly Salary (median)	\$3,729	\$3,399	\$3,883	\$3,992	\$4,064
Female	48.6%	50.1%	47.8%	45.9%	56.4%
Age < 30	17.5%	21.2%	15.6%	13.3%	22.5%
30 <= Age < 40	38.9%	36.1%	40.3%	42.0%	42.3%
40 <= Age < 50	28.2%	27.3%	28.7%	29.2%	17.8%
50 <= Age	15.4%	15.4%	15.4%	15.6%	17.4%
Faculty Member	53.3%	50.8%	54.5%	55.7%	45.0%
Business or Economics Department	3.5%	1.7%	4.4%	4.5%	5.0%
Other Quantitative Department	18.9%	19.0%	18.8%	17.8%	13.0%
Asian	7.6%	7.3%	7.8%	7.6%	9.0%
Black	2.6%	2.9%	2.4%	2.7%	2.8%
Hispanic	3.4%	3.4%	3.4%	3.7%	3.1%
White	84.6%	83.9%	84.9%	84.4%	83.6%
Other	1.8%	2.5%	1.5%	1.6%	1.6%
PhD	48.5%	39.7%	52.8%	57.8%	
Masters	29.5%	32.2%	28.2%	26.7%	
Bachelors	21.7%	28.1%	19.0%	15.5%	
	2,697	892	1,805	1,286	
% missing data	*42.4%*	*42.2%*	*42.4%*	*44.4%*	*100.0%*

Note: This table summarizes the characteristics of the sample of ORP participants for whom we observe salary, gender, age, job status, and self-reported ethnicity. We report statistics for: (1) full sample of participants joining ORP during Regime 1; (2) sample that chooses HIGH during Regime 1; (3) sample that chooses LOW, SMALL, or SMALLER during Regime 1; (4) sample that chooses LOW during Regime 1; and (5) full sample of participants joining ORP during Regime 2. Regime 1 begins in October 1996 and ends in October 2007. Regime 2 begins in November 2007 and ends in December 2009. Administrative data on the date of the choice between plans is left censored at January 1999. Job status and educational attainment are measured in the month that the participant begins working for OUS. Age and salary are measured in the month of the choice between plans or in January 1999. Faculty Member indicates whether participant i's job classification includes the string "Teach/Res". Business or Economics Department indicates whether participant i works in a business school or economics department. Other Quantitative Department indicates whether participant i's organizational description includes a reference to computer science, engineering, life science, mathematic, medicine, physical science, or a social science other than economics. We are missing data on educational attainment for 41.9% of the participants joining during Regime 1 and 100% of the participants joining during Regime 2 because these data were only collected by a subset of campuses and only through December 2004.

Table 3. Demand for HIGH by new ORP participants, October 1996 - October 2007

Dependent:	1 if new ORP participant chooses HIGH; 0 otherwise				
Date Range:	10/96 - 10/07	2/99 - 10/07	2/99 - 10/07	2/99 - 12/04	2/99 - 12/04
	(1)	(2)	(3)	(4)	(5)
Salary	-0.0273 ***	-0.0286 ***	-0.0270 ***	-0.0213 ***	-0.0192 ***
	(0.0030)	(0.0044)	(0.0046)	(0.0066)	(0.0072)
Female	-0.0178	-0.0165	-0.0169	-0.0466 *	-0.0485 *
	(0.0127)	(0.0179)	(0.0177)	(0.0242)	(0.0259)
Age [30, 40)	-0.0573 ***	-0.0664 ***	-0.0778 ***	-0.0407	-0.0629 *
	(0.0194)	(0.0213)	(0.0217)	(0.0311)	(0.0331)
Age [40, 50)	-0.0265	-0.0651 ***	-0.0852 ***	-0.0488	-0.0855 **
	(0.0292)	(0.0216)	(0.0216)	(0.0383)	(0.0381)
Age [50, 100]	-0.0059	-0.0908 ***	-0.0984 ***	-0.0906 **	-0.1191 ***
	(0.0567)	(0.0236)	(0.0255)	(0.0399)	(0.0402)
Asian	0.0105	0.0514 **	0.0513 *	0.0686 **	0.0732 *
	(0.0376)	(0.0265)	(0.0277)	(0.0356)	(0.0404)
Black	0.0435	0.0600	0.0774	0.0731	0.0985
	(0.0457)	(0.0552)	(0.0591)	(0.0859)	(0.0914)
Hispanic	0.0039	0.0190	0.0299	0.0420	0.0491
	(0.0344)	(0.0414)	(0.0429)	(0.0607)	(0.0640)
Other Ethnicity	0.0908 **	0.0725	0.0876	-0.0012	0.0316
	(0.0479)	(0.0612)	(0.0632)	(0.0873)	(0.1025)
Faculty	-0.0207	-0.0279 *	-0.0311	-0.0239	-0.0428
	(0.0131)	(0.0160)	(0.0198)	(0.0260)	(0.0285)
Business & Economics	-0.1386 ***	-0.0948 *	-0.0903 *	-0.1678 **	-0.1666 **
	(0.0403)	(0.0468)	(0.0493)	(0.0548)	(0.0539)
Other Quantitative	0.0166	0.0022	0.0011	-0.0362	-0.0302
	(0.0169)	(0.0201)	(0.0215)	(0.0296)	(0.0302)
PhD				-0.1060 ***	-0.1098 ***
				(0.0310)	(0.0359)
Masters				-0.0309	-0.0306
				(0.0279)	(0.0298)
Campus: Oregon State	-0.1263 ***	-0.1306 ***	-0.1395 ***	-0.2064 ***	-0.2192 ***
	(0.0167)	(0.0230)	(0.0245)	(0.0290)	(0.0320)
Campus: Portland State	0.0147	0.0319	0.0242	-0.0016	-0.0055
	(0.0217)	(0.0255)	(0.0251)	(0.0347)	(0.0338)
Campus: Oregon Inst. of	0.0713	-0.0554	-0.0576	0.0313	0.0435
Technology	(0.0868)	(0.0454)	(0.0462)	(0.0536)	(0.0520)
Campus: Eastern Oregon	-0.0218	-0.0571	-0.0598		
	(0.0490)	(0.0515)	(0.0502)		
Campus: Southern Oregon	-0.1252 ***	-0.1445 ***	-0.1542 ***		
	(0.0293)	(0.0323)	(0.0321)		
Campus: Western Oregon	-0.0252	-0.0965 *	-0.1087 **		
	(0.0568)	(0.0452)	(0.0438)		
Office of the Chancellor	-0.1645 ***	-0.2021 ***	-0.2228 ***		
	(0.0440)	(0.0431)	(0.0365)		
Date of choice fixed effects?	---	---	Yes	---	Yes
N	4,680	3,302	3,302	1,554	1,554
Pseudo-R2	0.0385	0.0482	0.0859	0.0729	0.1221

Note: In this table, we predict demand for brokers by new ORP participants. The dependent variable equals one if participant i chooses HIGH and zero if she chooses SMALL, SMALLER, or LOW. The sample in column (1) includes all ORP participants joining between October 1996 (when ORP is created) and October 2007 (when HIGH is no longer available to new ORP participants). Because choices made between October 1996 and January 1999 are recorded as January 1999, the sample period in other columns begins in February 1999. Because data on participant i's educational attainment were only collected through December 2004 and only by four of the campuses, the sample period in columns (4) and (5) end in December 2004, and the sample is limited to participants employed by Oregon Institute of Technology, Oregon State, Portland State, or University of Oregon for whom we observe data on educational attainment. Demographic controls include salary, gender, age, self-declared ethnicity (the omitted category is "White"), and educational attainment (the omitted category is "Bachelors"). We also control for whether the participant is faculty or staff, and for whether we classify the department as business and economics, quantitative but not business or economics, and all of the rest. To control for economic conditions in the month of the choice, columns (3) and (5) include a separate fixed effect for each year-month. To control for potential differences in preferences across employers, we include a separate fixed effect for each campus, and for the Office of the Chancellor. 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 during Regime 1 from a survey of current ORP participants

Panel A. Testing for differences in reliance upon financial advisers 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?			
	N	Yes	N	Agree or Strongly Agree	N	My own research and knowledge of investing	Recommendation of adviser	Recommendation of friends, family, or co-workers
HIGH	259	58.7%	146	24.7%	214	21.5%	74.3%	4.2%
Other	599	36.6%	211	39.8%	497	45.3%	45.1%	9.7%
Difference		22.1%		-15.2%		-23.8%	29.2%	-5.5%
P-value		0.000		0.003		0.000	0.000	0.013

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

How Often Do You Meet With Your HIGH Adviser?	
Never	15.0%
Once a year	55.9%
Twice a year	21.6%
More than twice	7.5%
N	213

When you receive investment advice, do you usually implement the advice:	LOW	HIGH
"Within two weeks"	27.1%	43.4%
"Within two months"	34.7%	30.9%
"Within the year"	23.0%	17.6%
"Never"	15.2%	8.2%
N	553	233

"I understand how much money my adviser earns on my account"	
Strongly Agree	8.0%
Agree	15.1%
Disagree	50.9%
Strongly Disagree	25.9%
N	212

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
HIGH	296	69.9%	291	57.4%	295	72.5%	297	80.8%
Other	642	38.2%	641	60.4%	644	74.8%	648	87.2%
Difference		31.8%		-3.0%		-2.3%		-6.4%
P-value		0.000		0.390		0.456		0.011

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

	Financial Literacy		Choice between jobs with certain versus uncertain income					
	N	Fraction of Four Financial Literacy Questions Correct	N	Fraction Who Prefer Job 2 50% up 20% 50% down 15%	N	Fraction Who Prefer Job 2 50% up 20% 50% down 10%	N	Fraction Who Prefer Job 2 50% up 20% 50% down 5%
HIGH	240	90.0%	164	17.7%	162	45.1%	176	77.3%
Other	538	92.8%	384	20.3%	367	51.2%	416	82.9%
Difference		-2.8%		-2.6%		-6.1%		-5.7%
P-value		0.061		0.476		0.192		0.110

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 980 participants who chose HIGH (313) or one of the other three providers (667) between October 1996 and October 2007. The survey response rates are similar for the two groups: 17.0% (313/1843) for HIGH and 16.8% (667/3964) for the other three providers. The fact that the survey did not require completion of all questions explains the variation in sample size from question to question. For each question, we analyze all non-missing answers. P-values are estimated using standard errors that are robust to heteroscedasticity.

Table 5. Demand for Default Investment Option, by Provider and Regime

Sample period:		Regime 1		Regime 2	
Provider	Default	N	Invest 100% in Default?	N	Invest 100% in Default?
Panel A. Sample of new participants for which we observe portfolio holdings in month 6					
HIGH	Fixed annuity	1,492	2.9%		
LOW	Money market fund	2,341	9.5%	256	21.5%
NEW	Target-date fund			272	64.0%
		3,833	6.9%	528	43.4%
Panel B. Subsample of new participants for which we can estimate Pr(HIGH) in column (2) of Table 3					
HIGH	Fixed annuity	862	2.0%		
LOW	Money market fund	1,465	12.6%	240	21.7%
NEW	Target-date fund			256	65.2%
		2,327	8.7%	496	44.2%

Note: In this table, we report the fraction of new ORP participants that invest 100% of their ORP contribution in the default investment option 5 months after their first ORP contribution. Because we lack portfolio-level data from SMALL and SMALLER, Panel A is restricted to participants that originally chose to invest through HIGH, LOW, or NEW. Panel B is restricted to those new ORP participants for which the date of the choice is not censored at January 1999 and for whom we possess the demographic data required to estimate Pr(HIGH) in column (2) of Table 3. In each panel, we distinguish between Regime 1, when new ORP participants can choose to invest through HIGH, and Regime 2, when they cannot.

Table 6. Using Predicted Demand for Brokers to Predict Demand for Default Investment Options

Dependent:	1 if new participant contributes 100% to default investment option in month 6							
Sample Period:	Regime 1		Regime 2					
ORP Providers:	HIGH or LOW		LOW or NEW		NEW only		LOW only	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pr(HIGH)	-0.0140		0.5362 ***		0.7644 ***		0.0871	
	(0.0516)		(0.1537)		(0.2314)		(0.2687)	
Pr(HIGH) in top quartile?		0.0182		0.1207 *		0.1687 *		-0.0532
		(0.0142)		(0.0598)		(0.0869)		(0.0966)
Pr(HIGH) in bottom quartile?		0.0085		-0.0711		-0.1065 *		-0.0780
		(0.0123)		(0.0414)		(0.0583)		(0.0681)
Constant	0.0912 ***	0.0799 ***	0.2871 ***	0.4379 ***	0.4289 ***	0.6459 ***	0.1920 **	0.2466 ***
	(0.0162)	(0.0056)	(0.0443)	(0.0194)	(0.0676)	(0.0293)	(0.0762)	(0.0270)
P-value from test that coefficient on Pr(HIGH) equals one	0.0000 ***		0.0066 ***		0.3201		0.0030 ***	
P-value from test that coefficients are equal for top and bottom quartile		0.5285		0.0048 ***		0.0083 ***		0.8161
Date of choice fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,327	2,327	496	496	256	256	240	240
R2	0.0705	0.0712	0.0746	0.0773	0.1429	0.1501	0.0813	0.0876

Note: In this table, we predict whether new ORP participant i is contributing 100% of her retirement contributions to the provider j's default investment option five months after her first contribution to provider j. Estimation is via OLS. We estimate separate specifications for participants who have access to HIGH (i.e., participants whose first contribution is before 10/07) and participants who do not have access to HIGH (i.e., participants whose first contribution is after 10/07). The independent variable of interest is the predicted probability that participant i chooses HIGH based on the estimated coefficients in Column (2) of Table 3. Because Column (2) of Table 3 is restricted to participants for whom we observe the date of the choice, we are able to include a separate fixed effect for the year-month of the choice. The last two columns are restricted to the subset of new participants who choose to invest through NEW, which offers target-date funds as its default investment option. 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 7. Comparing Actual Portfolios to Counterfactual Portfolios Based on Target-Date Funds, 1999-2009

Panel A. HIGH

	Actual				Target-Date Fund Benchmark			
	Annual Return	Volatility of Monthly Return	CAPM Beta	Broker Fee	Annual Return	Volatility of Monthly Return	CAPM Beta	Broker Fee
1999	29.36%	3.94%	0.795	0.93%	24.53%	3.14%	0.695	0.00%
2000	-13.60%	5.98%	0.854	0.93%	-2.87%	4.07%	0.758	0.00%
2001	-18.76%	7.00%	1.118	0.93%	-9.32%	4.46%	0.723	0.00%
2002	-18.11%	4.56%	1.035	0.93%	-14.17%	3.97%	0.690	0.00%
2003	23.32%	2.69%	0.753	0.92%	25.51%	2.37%	0.673	0.00%
2004	8.92%	2.18%	0.808	0.91%	9.80%	2.01%	0.837	0.00%
2005	4.52%	2.06%	0.857	0.91%	8.09%	2.04%	0.788	0.00%
2006	10.08%	1.61%	0.788	0.91%	12.23%	1.87%	0.942	0.00%
2007	4.79%	2.30%	0.811	0.85%	8.87%	2.40%	0.834	0.00%
2008	-31.98%	5.72%	0.792	0.85%	-34.86%	5.94%	0.904	0.00%
2009	25.66%	5.14%	0.814	0.86%	29.78%	5.30%	0.819	0.00%
1999-2009	1.85%	3.81%	0.852	0.90%	4.83%	3.38%	0.796	0.00%

Panel B. LOW

	Actual				Target-Date Fund Benchmark			
	Annual Return	Volatility of Monthly Return	CAPM Beta	Broker Fee	Annual Return	Volatility of Monthly Return	CAPM Beta	Broker Fee
1999	19.87%	2.88%	0.704	0.00%	25.17%	3.20%	0.709	0.00%
2000	-7.82%	4.19%	0.683	0.00%	-3.15%	4.14%	0.772	0.00%
2001	-10.71%	4.70%	0.728	0.00%	-9.46%	4.50%	0.730	0.00%
2002	-14.41%	3.73%	0.731	0.00%	-14.49%	4.04%	0.702	0.00%
2003	20.00%	1.97%	0.584	0.00%	25.88%	2.40%	0.685	0.00%
2004	8.67%	1.52%	0.567	0.00%	9.83%	2.02%	0.843	0.00%
2005	6.22%	1.50%	0.609	0.00%	8.14%	2.05%	0.793	0.00%
2006	10.74%	1.26%	0.559	0.00%	12.20%	1.87%	0.940	0.00%
2007	8.03%	1.60%	0.618	0.00%	8.86%	2.40%	0.831	0.00%
2008	-22.20%	3.73%	0.538	0.00%	-34.90%	5.95%	0.905	0.00%
2009	15.32%	3.20%	0.532	0.00%	29.80%	5.32%	0.822	0.00%
1999-2009	3.14%	2.56%	0.599	0.00%	4.86%	3.50%	0.818	0.00%

Note: In this table, we summarize the actual and counterfactual portfolios of participants who choose to invest through HIGH or LOW during Regime 1. The sample includes all participants for whom we observe positive holdings of at least one fund at the beginning of year t, and for whom we observe a birth year and month. "Annual return" is the average annual buy-and-hold return that participant i would have earned in year t if she neither changed her holdings during year t nor made any additional retirement contributions to ORP. For the actual portfolios, this measure is equally highly correlated with realized portfolio returns of broker clients and self-directed investors. To determine a participant's counterfactual allocation, we assume that her target retirement date is the year in which she turns 65, and then pick the Fidelity TDF with the closest target retirement date (2010, 2020, 2030, and 2040). "CAPM Beta" is the weighted-average CAPM beta of the funds held at the beginning of year t. Fund-level betas are estimated using fund-level returns over the prior 12 months. "Volatility of Monthly Returns" is the standard deviation of monthly returns during calendar year t, calculated from monthly portfolio-level returns. "Broker fee" is the average broker fee paid by broker clients in year t. It is zero for LOW and for the counterfactual portfolios based on TDFs.

Table 8. Testing for Differences in Risk and Return, HIGH versus LOW versus Target-Date Funds, 1999-2009

Dependent:	Annual Portfolio Return		Volatility of Monthly Returns		CAPM Beta		6-Factor Alpha		Sharpe Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Comparing Actual Portfolios to Counterfactual Portfolios Based on Target-Date Funds										
HIGH	-0.0321 ***		0.0037		0.0532		-0.0211 **		-0.1433 **	
	(0.0110)		(0.0027)		(0.0552)		(0.0104)		(0.0572)	
LOW		-0.0172		-0.0093 ***		-0.2168 ***		-0.0088		-0.1197
		(0.0287)		(0.0029)		(0.0420)		(0.0066)		(0.0874)
Year fixed effects?	---	---	---	---	---	---	---	---	---	---
N	5,846	15,203	5,846	15,203	5,001	15,202	4,212	15,144	5,846	15,203
R2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B. Comparing Actual Portfolios of HIGH and LOW										
HIGH?	-0.0145	-0.0196	0.0114 ***	0.0002	0.2312 ***	-0.0572	-0.0119	-0.0114	-0.3129	0.0745
	(0.0209)	(0.0136)	(0.0023)	(0.0033)	(0.0272)	(0.0670)	(0.0125)	(0.0104)	(0.1940)	(0.3511)
Pr(HIGH) * HIGH?		0.0120		0.0189 **		0.4977 ***		-0.0011		-0.8476
		(0.0360)		(0.0074)		(0.1502)		(0.0100)		(0.5187)
Pr(HIGH) * LOW?		-0.0028		-0.0146 ***		-0.3638 ***		0.0003		0.2816
		(0.0339)		(0.0035)		(0.0610)		(0.0051)		(0.2769)
P-values from test that coefficients are equal on interaction terms		0.8047		0.0000 ***		0.0000 ***		0.8855		0.0648 *
Year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,049	21,049	21,049	21,049	20,203	20,203	19,437	19,437	21,049	21,049
R2	0.7752	0.7752	0.4584	0.4637	0.1347	0.1469	0.1547	0.1547	0.0427	0.0429

Note: The unit of observation is the portfolio of ORP participant i in calendar year t. The sample period is 1999-2009. Portfolio characteristics include the portfolio's annual after-fee return, volatility of monthly returns, lagged CAPM beta, six-factor alpha, and Sharpe ratio. Characteristics of actual portfolios are estimated from beginning of the year holdings, assuming no additional retirement contributions during year t. Characteristics of counterfactual portfolios are based on the Fidelity TDF to which participant i is assigned. The OLS regressions in Panel A separately test for differences between the actual and counterfactual portfolios of HIGH and LOW investors. The dependent variable in each regression is the difference between the characteristics of participant i's actual and counterfactual portfolios. The numerator of the Sharpe ratio is the difference in monthly returns and the denominator is the standard deviation of the difference in monthly returns. The OLS regressions in Panel B compare the portfolios of HIGH and LOW investors. The dependent variable is the characteristics of participant i's actual portfolio. 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. We report the p-value from the test that the coefficients on the two interaction terms are equal. To allow for correlations both in annual portfolio returns across participants in year t and in participant i's annual portfolio returns across years, we cluster standard errors on calendar year t and participant i. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 9. Allocation of Retirement Contributions Across Available Funds

Dependent:	Fraction of Retirement Contributions Allocated to Fund j					
Sample Period:	*Month 1 (1st ORP Contribution)*			*Month 24*		
Sample of Funds:	*All*	*All*	*HIGH Equity*	*All*	*All*	*HIGH Equity*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Lagged Return * HIGH	0.461 ***	0.530 ***	0.463 ***	-0.057	-0.053 ***	-0.062 ***
	(0.042)	(0.053)	(0.000)	(0.071)	(0.000)	(0.000)
Not Broker Fee * HIGH	-23.985 ***	-24.584 ***	-31.426 ***	-19.865 ***	-22.993 ***	-26.462 ***
	(1.087)	(1.316)	(0.064)	(1.648)	(0.063)	(0.057)
Broker Fee	41.645 ***	46.152 ***	70.595 ***	39.173 ***	44.572 ***	65.175 ***
	(3.105)	(3.141)	(0.043)	(4.396)	(0.048)	(0.048)
Lagged Return * LOW	0.112	1.139 ***		0.320 ***	1.270 ***	
	(0.069)	(0.348)		(0.114)	(0.000)	
Not Broker Fee * LOW	-38.388 **	152.369 **		-45.005 ***	-21.857 ***	
	(15.491)	(61.608)		(10.046)	(0.047)	
Ho: Same Sensitivity to Lagged Return?	0.000 ***	0.060 *		0.002 ***	0.000 ***	
Ho: Same Sensitivity to Not Broker Fee?	0.348	0.004 ***		0.011 **	0.000 ***	
Fund-level controls?	Yes	Yes	Yes	Yes	Yes	Yes
Provider-date fixed effects?	Yes	---	---	Yes	---	---
Provider-broad category-date fixed effects?	---	Yes	---	---	Yes	---
Provider-narrow category-date fixed effects?	---	---	Yes	---	---	Yes
N	74,547	74,547	34,672	61,574	61,574	26,704
Adj. R2	0.2197	0.2656	0.4075	0.2008	0.2527	0.4046

Note: In this table, we test whether the fraction of participant i's retirement contribution 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 is restricted to ORP participants who joined during Regime 1 and chose to invest through HIGH or LOW. It 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 a comparable 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 for LOW), and the fund's annual fee minus the broker fee. (No fund is simultaneously available through both providers.) In specifications (1) and (3), we include provider-by-date fixed effects, and dummy variables for the broad investment category of each fund: annuity, bond, domestic equity, international equity, etc. In the other specifications, we include provider-by-category-by-date fixed effects. In columns (2) and (4), we consider the full set of investment options and interact the provider-by-date fixed effects with dummy variables for the full set of broad investment categories. In columns (3) and (6), we restrict the sample to domestic equity funds available through HIGH and interact the provider-by-date fixed effects with narrow (Lipper) investment category fixed effects (i.e., large-cap growth, mid-cap value, small-cap core, etc.) In addition to controlling for fund investment objectives, returns, and fees, we control for fund j's lagged turnover and whether it is passively managed. We exclude participants who allocate 100% of their retirement contribution to the default investment option. All variables are scaled so that 1.000 equals 100%. Standard errors are clustered on date. We report the p-value of the hypotheses tests that the sensitivity to lagged return and non-broker fee are equal for HIGH and LOW. Standard errors are clustered on the date of participant i's contribution. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table A1. Overview of Actual Investment Menus

	HIGH			LOW			NEW
Asset Class	Beginning Regime 1	End Regime 1	End Regime 2	Beginning Regime 1	End Regime 1	End Regime 2	All Regime 2
Money Market	1	2	2	1	1	1	1
Fixed Annuity	2	2	2	1	1	1	1
Fixed Income	6	9	9	2	2	2	5
Balanced	5	11	10	1	1	1	0
Target Date	0	0	0	0	0	0	12
U.S. Equity	21	31	31	2	9	9	16
Global	5	7	7	2	3	3	3
Real Estate	0	0	0	1	2	2	0
Passively Managed	3	4	4	1	2	2	4
Actively Managed	37	58	57	9	17	17	34
Managed by Provider	16	52	51	10	19	19	16
Not Managed by Provider	24	10	10	0	0	0	22
Total Number of Options	**40**	**62**	**61**	**10**	**19**	**19**	**38**

Note: This table summarizes the investment menus available through HIGH, LOW, and NEW at the beginning and end of Regime 1 and the end of Regime 2. HIGH makes numerous changes to its investment menu during Regime 1, increasing the total number of investment options, but decreasing the number of investment options managed by firms other than HIGH. LOW offers the same ten investment options between October 1996 and June 2007, adding nine new investment options in July 2007. NEW offers the same menu during all of Regime 2.

Table A2. Overview of Investment Menus in 2002

Asset Class	HIGH	LOW	SMALL	SMALLER
Money Market	1	1	1	1
Fixed Annuity	0	1	0	0
Fixed Income	1	2	2	2
Balanced	0	1	3	1
Target Date	0	0	0	0
U.S. Equity	9	2	4	4
Global	2	2	1	2
Real Estate	0	1	0	0
Passively Managed	1	1	0	0
Actively Managed	12	9	11	10
Managed by Provider	1	10	11	10
Not Managed by Provider	12	0	0	0
Total Number of Options	**13**	**10**	**11**	**10**

Note: To help employees choose between PERS and ORP, the Oregon University System listed some of the investment options available to new participants through each provider. With the exception of LOW, these lists corresponded to subsets of the actual investment menus. In this table, we summarize the types of investment options shown to employees for each provider in 2002.

Table A3. Demand for ORP versus PERS

Dependent:	1 if OUS employee chooses PERS				
Date Range:	10/96 - 10/07	2/99 - 10/07	2/99 - 10/07	2/99 - 12/04	2/99 - 12/04
	(1)	(2)	(3)	(4)	(5)
Salary					
Female	0.0173	0.0009	0.0024	-0.0072	-0.0049
	(0.0141)	(0.0068)	(0.0068)	(0.0105)	(0.0110)
Age [30, 40)	-0.1635 ***	-0.1250 ***	-0.1094 ***	-0.0596 ***	-0.0512 ***
	(0.0338)	(0.0145)	(0.0113)	(0.0186)	(0.0163)
Age [40, 50)	-0.1505 ***	-0.0776 ***	-0.0727 ***	0.0000	-0.0013
	(0.0577)	(0.0137)	(0.0122)	(0.0181)	(0.0178)
Age [50, 100]	-0.0378	0.0247 **	0.0158	0.0998 ***	0.0824 ***
	(0.0544)	(0.0108)	(0.0120)	(0.0172)	(0.0171)
Asian	0.0032	-0.0169	-0.0123	0.0155	0.0132
	(0.0182)	(0.0119)	(0.0108)	(0.0172)	(0.0162)
Black	-0.0545 **	-0.0674 ***	-0.0690 ***	-0.1020 ***	-0.1057 ***
	(0.0221)	(0.0220)	(0.0248)	(0.0399)	(0.0447)
Hispanic	0.0338 ***	0.0297 **	0.0338 **	0.0346	0.0238
	(0.0124)	(0.0140)	(0.0127)	(0.0229)	(0.0225)
Other Ethnicity	0.0225	0.0124	0.0187	0.0196	0.0020
	(0.0185)	(0.0197)	(0.0184)	(0.0310)	(0.0318)
Faculty	-0.0473 **	-0.0316	-0.0323 *	0.0445 *	0.0323
	(0.0246)	(0.0247)	(0.0190)	(0.0243)	(0.0222)
Business & Economics	-0.0999 ***	-0.0738 ***	-0.0630 **	-0.0633 *	-0.0522
	(0.0282)	(0.0304)	(0.0275)	(0.0410)	(0.0374)
Other Quantitative	-0.0707 ***	-0.0668 ***	-0.0470 ***	-0.0243 *	-0.0186
	(0.0081)	(0.0101)	(0.0092)	(0.0140)	(0.0146)
PhD				-0.2506 ***	-0.2069 ***
				(0.0322)	(0.0226)
Masters				-0.0390 **	-0.0390 **
				(0.0191)	(0.0164)
Campus: Oregon State	0.0130	0.0125	0.0246 *	0.0493 ***	0.0600 ***
	(0.0121)	(0.0145)	(0.0124)	(0.0193)	(0.0138)
Campus: Portland State	0.1387 ***	0.1184 ***	0.1147 ***	0.1288 ***	0.1275 ***
	(0.0177)	(0.0116)	(0.0094)	(0.0168)	(0.0152)
Campus: Oregon Inst. of	-0.0154	0.0095	0.0238	0.0401	0.0613 **
Technology	(0.0292)	(0.0248)	(0.0186)	(0.0338)	(0.0228)
Campus: Eastern Oregon	0.0750 ***	0.0609 ***	0.0772 ***		
	(0.0175)	(0.0171)	(0.0136)		
Campus: Southern Oregon	0.1573 ***	0.1280 ***	0.1318 ***		
	(0.0247)	(0.0139)	(0.0091)		
Campus: Western Oregon	0.0691 ***	0.0669 ***	0.0806 ***		
	(0.0140)	(0.0166)	(0.0126)		
Office of the Chancellor	-0.0628 *	-0.0755 *	-0.0526		
	(0.0370)	(0.0465)	(0.0460)		
Date of choice fixed effects?	---	---	Yes	---	Yes
N	20,398	16,395	16,395	6,898	6,898
Pseudo-R2	0.0705	0.0608	0.1762	0.0897	0.2257

Note: Probit specifications mirror those in Table 3. Dependent variable equals one if OUS employee i chooses PERS as his retirement plan and zero if he chooses ORP. Independent variables are the same as in Table 3, except that we cannot include monthly salary because we only observe monthly salary for the subset of employees who choose ORP. 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 ***.