Is Conflicted Investment Advice Better than No Advice?*

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ABSTRACT

Measuring the causal impact of financial advice on client portfolios requires knowledge of how clients would have invested in the absence of advice. We use time-series variation in access to brokers by new defined contribution plan participants to model demand for advice and to identify plausible counterfactual portfolios of broker clients. When brokers are unavailable, demand for target date funds (TDFs) increases differentially among new participants with high predicted demand for advice. Broker clients earn significantly lower alphas and Sharpe ratios than matched TDF portfolios, while bearing similar levels of risk and avoiding average annual broker fees of 0.90%. On the other hand, when brokers are available and TDFs are not, participants with high predicted demand for advice are much less likely to invest exclusively in a money market fund when they invest through a broker.

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I. Introduction

Providing financial advice to investors is a multibillion-dollar industry. Because investment returns are volatile, however, it can be difficult for investors to distinguish good *ex ante* recommendations from bad. This fact raises important questions about the quality of the recommendations that clients receive from their brokers.[1,2] Anagol, Cole, and Sarkar (2016), Christoffersen, Evans, and Musto (2013), Hackethal, Inderst, and Meyer (2012), Hoechle, Ruenzi, Schaub, and Schmid (2015), and Mullainathan, Nöth, and Schoar (2012) use a wide variety of empirical strategies to document that broker recommendations reflect brokers' self-interests.[3] While these studies indicate that there is scope for brokers to improve the quality of their recommendations, the literature is silent on clients' counterfactual outcomes in the absence of conflicted advice.[4]

In a rational choice model, clients benefit from 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, clients would benefit from unbiased recommendations. Nevertheless, some clients may rationally prefer biased (expensive) broker recommendations to no recommendations. For example, in Gennaioli, Shleifer, and Vishny (2015), trusted brokers increase clients' equity allocations above counterfactual levels of zero, allowing clients to earn an equity risk premium and allowing brokers to charge a fee that splits the gains from trade. The lower the expected utility associated with a client's counterfactual portfolio, the larger the potential gain from trade, and the more likely that the client benefits from recommendations, even when they are biased. Moreover, the lower the financial sophistication of broker clients, the more likely that this situation is to arise. 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 recommendations.

The lack of existing research on the net benefits of brokers to their clients reflects the lack

[1] Note that because the financial advice in our setting comes from brokers, we refer to financial advisors as brokers and we refer to their advice as broker recommendations.
[2] 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.
[3] Bergstresser, Chalmers, and Tufano (2009) and Del Guercio and Reuter (2014) use fund-level data to show that broker-sold mutual funds underperform direct-sold funds.
[4] For example, measuring the net benefit of financial advice in Von Gaudecker (2015) requires measures of counterfactual portfolio diversification. Similarly, while Foerster, Linnainmaa, Melzer and Previtero (2017) use changes in broker-client relationships to demonstrate that broker recommendations have a causal impact on client portfolios, they lack the data on counterfactual portfolios required to measure the net benefit of brokers within their sample of investors. More generally, Hung and Yoong (2013) discuss the limitations of "advice" studies in many contexts due to selection and reverse causality. Their approach is to combine survey data with controlled lab experiments.

of data on clients' counterfactual portfolios. The innovation in this paper is that we are able to identify plausible counterfactual portfolios for broker clients within a single defined contribution (DC) retirement plan. An ideal experiment would identify the counterfactual portfolios of broker clients by withholding recommendations from a randomized sample of real-world investors seeking 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 the reluctantly self-directed investors to identify the counterfactual portfolios of the broker clients. While retirement plan providers in the United States are prohibited from running this type of experiment on plan participants, we are able to exploit time-series variation in access to brokers by new plan participants.

Our empirical setting is 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.[5] Participants who choose to invest through the ORP must then choose an investment provider to which their retirement contributions will be sent. Between October 1996 and October 2007, four providers were available to participants: HIGH, whose network of brokers provide face-to-face recommendations, and three participant-directed options: LOW, SMALL, and SMALLER. Effective November 2007, new participants were limited to investing through either LOW or NEW, neither of which provide the same type of personalized attention that HIGH continues to provide to its legacy participants. Our empirical strategy relies on both the availability of brokers and non-brokers through October 2007 and the loss of access to brokers by new participants in November 2007. With OUS's help, we were able to match administrative data on ORP participants with retirement account-level data from HIGH, LOW, and NEW.[6,7] Our account-level data end in December 2009.

We begin by using the availability of HIGH until October 2007 to study demand for broker recommendations within our DC retirement plan.[8] We find that demand for HIGH is negatively

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

[6] OUS asked us not to disclose the names of HIGH, LOW, SMALL, SMALLER, or NEW.

[7] Table 1 shows that between October 1996 and October 2006, 82.5% of ORP participants choose to invest through 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 efforts.

[8] Because the employer makes all retirement contributions in ORP, broker recommendations in our setting are limited to asset allocation and fund selection. This fact allows us largely to abstract from potentially valuable advice that brokers may provide in other settings with respect to taxes, insurance, or savings rates.

correlated with age, salary, and educational attainment, and is significantly lower among participants working in an economics department or business school. These patterns suggest that ORP participants are more likely to seek broker recommendations when they have lower levels of financial literacy or less investment experience. In our preferred specification for predicting demand for HIGH, we find that 39.2% of participants with predicted demand in the top quartile choose to invest through HIGH versus 14.8% of those in the bottom quartile. To provide more direct evidence on the demand for broker recommendations, we administer an online survey to ORP participants, asking them to weigh the factors that led them to choose their initial ORP provider. The survey results confirm that demand for HIGH is primarily driven by demand for face-to-face help with asset allocation. These findings increase our confidence that client portfolios reflect broker recommendations.[9] More importantly, the fact that HIGH is chosen by those seeking advice on asset allocation and fund selection raises significant questions about how these participants would have invested in the absence of broker recommendations. In particular, it argues against constructing counterfactual portfolios for broker clients from either the actual portfolios of self-directed investors or commonly used academic benchmarks, such as low-cost index funds.

Next, we study whether default investment options can substitute for broker recommendations in the population that we predict are most likely to use a broker. We exploit the fact that after October 2007 participants joining ORP no longer had the option to choose a broker. Using account-level data from HIGH, LOW, and NEW, we identify participants who, after six months, continue to allocate 100% of their retirement contribution to their provider's default investment option. Between January 2006 and October 2007, demand for the default option ranges from 1% for HIGH, where the default is a fixed annuity, to 22% for LOW, where it is a money market fund. Between November 2007 and December 2009, when new participants lack access to brokers, overall demand for default investment options by new participants increases significantly. It remains 22% for LOW, where the default remains a money market fund, but jumps to 65% for NEW, where the default is a Fidelity Freedom target date fund (TDF). These changes are broadly consistent with participants viewing TDFs, which relieve investors of the need to make asset allocation or fund selection decisions, as substitutes for brokers. To provide more direct evidence on substitution of TDFs for brokers, we test whether the model that predicts demand for HIGH in the earlier

[9] In Appendix D, we study the allocation of client contributions across funds on HIGH's investment menu. Similar to Christoffersen, Evans, and Musto (2013), we find that investment options paying higher broker fees receive significantly higher contributions from broker clients.

period also predicts demand for TDFs in the later period.[10] We find that 47.5% of new participants with top-quartile predicted demand for HIGH choose to invest in a TDF versus 28.7% of new participants with bottom-quartile predicted demand for HIGH. While this spread is slightly smaller than when we use predicted demand for HIGH to explain across-participant variation in demand for HIGH, it remains economically significant.

We use three empirical strategies to estimate the causal effect of brokers on their clients' portfolios. We begin by comparing actual portfolios of broker clients to counterfactual portfolios based on Fidelity Freedom TDFs. Based on our findings above, these are the counterfactual portfolios that many broker clients would have held if ORP had dropped HIGH and added NEW in 1999, when our data on actual portfolios begin. We consider the full sample of broker clients and the subsample with top-quartile predicted demand for HIGH. In both samples, broker clients earned significantly lower risk-adjusted returns and lower Sharpe ratios than they would have earned if they had been invested in the age-specific Fidelity TDFs offered by NEW.[11] We can attribute approximately half of the underperformance to broker fees, which average 90 basis points per year. The remainder is due to differences in the risk-adjusted, after-fee returns of the actual and counterfactual investment options.

Our second empirical strategy compares the actual portfolios of participants with high predicted demand for HIGH who join ORP in the months before and after November 2007, when HIGH is removed from the set of available providers. Although this comparison is necessarily limited to the last calendar year of our sample period (2009), we find no evidence that participants with high predicted demand for brokers were harmed by the lack of access to broker recommendations. Instead, we find that the Sharpe ratios of the high-broker-demand portfolios constructed without brokers are both higher and less variable than the Sharpe ratios of the high-broker-demand portfolios constructed by participants who had access to brokers. The fact that these findings continue to hold when we exclude portfolios based on TDFs suggests that few if any participants with high predicted demand for broker recommendations would have been harmed if ORP had dropped HIGH and added NEW before the actual regime change in October 2007.

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[10] Our approach 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 under diversification (which is likely to be a second order problem when investing in mutual funds in a retirement account), failure to rebalance, and the disposition effect.

[11] Fidelity Freedom funds were introduced in 1996 and, as Balduzzi and Reuter (2018) document, Fidelity TDFs had the largest share of the TDF market throughout our sample period. The Fidelity Freedom funds that we use as counterfactual portfolios have relatively high (acquired) fees because they invest in Fidelity's actively managed funds.

Our final empirical strategy is motivated by Gennaioli, Shleifer, and Vishny (2015), who assume that trusted brokers reduce the disutility associated with bearing financial risk. Their key prediction is that actual portfolios of broker clients will hold more equity than counterfactual portfolios constructed without access to brokers. To test this prediction, we focus only on participants who had the option to invest through HIGH. By interacting 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, we compare the portfolio characteristics of participants who are predicted to invest through brokers and do to those of participants who are predicted to invest through brokers but do not. Our identifying assumption is that participants with high predicted broker demand who do not choose to invest through a broker are making a mistake. To the extent that participants not matching with brokers are simply more comfortable bearing market risk on their own, our specification will underestimate the impact of brokers on risk taking. Despite this caveat, 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 but do not. These findings lend support to the key assumption underlying Gennaioli et al.

We make three contributions to the literature on financial advice. First, we highlight the need to benchmark actual broker client portfolios against counterfactual portfolios constructed without access to brokers. Second, by showing that demand for broker recommendations within our setting is driven by demand for advice on asset allocation and fund selection, we challenge the common implicit assumption that it is appropriate to use low-cost index funds or the actual portfolios of self-directed investors as proxies for the counterfactual portfolios of broker clients. Third, and most importantly, we are the first paper to benchmark actual client portfolios against plausible counterfactual portfolios. Doing so reveals that the answer to "Is Conflicted Investment Advice Better than No Advice?" depends on the institutional setting. Our first two empirical strategies, which lead us to conclude that the answer is no, rely on the fact that ORP added TDFs (through NEW) at the same time that it removed HIGH. Our final empirical strategy, on the other hand, highlights a potentially positive impact of broker recommendations on client portfolio risk levels in institutional settings that lack well-designed default investment options. Consequently, had ORP simply removed HIGH without adding NEW, we likely would have observed much lower levels of portfolio risk among the reluctantly self-directed investors.

Figure 1: Framework for Advice

	Receive Advice? Yes	Receive Advice? No
Seek Advice? Yes	**(Y, Y)** Broker client's actual portfolio	**(Y, N)** Broker client's counterfactual portfolio
Seek Advice? No	**(N, Y)** Self-directed investor receives unsolicited advice	**(N, N)** Self-directed investor's actual portfolio

II. Empirical Framework and Literature Review

To highlight how our paper contributes to the growing literature on financial advice, we begin with a stylized model of investors who differ along two dimensions. The first dimension is whether they seek recommendations on asset allocation and fund selection. The second dimension is whether they receive (and follow) these recommendations. Figure 1 illustrates the resulting four cases. Actual broker clients, who both seek and receive recommendations, are classified as (Yes, Yes). Investors who seek but do not receive recommendations are classified as (Yes, No). The portfolios of these reluctantly self-directed investors reveal how would-be broker clients would have invested in the absence of broker recommendations; the empirical challenge is to identify these portfolios in real-world data. Intentionally self-directed investors are classified as (No, No). To the extent that intentionally self-directed investors have greater financial knowledge or investment experience than investors seeking broker recommendations, the real-world portfolios of self-directed investors will be poor proxies for the counterfactual portfolios of broker clients.[12]

Broker client *i* benefits from receiving (and following) broker recommendations whenever the expected utility of receiving these recommendations exceeds the expected utility of not receiving them:

$$E[U_i(Y, Y)] - E[U_i(Y, N)] > 0.$$

If we distinguish unbiased recommendations from biased recommendations, it follows mechanically that broker clients receive higher expected utility from the unbiased recommendations:

$$E[U_i(Y, Y_{Unbiased})] - E[U_i(Y, N)] > E[U_i(Y, Y_{Biased})] - E[U_i(Y, N)].$$

[12] Behrman, Mitchell, Soo, and Bravo (2010) find that financial literacy has a causal impact on wealth accumulation, and that this impact increases with educational attainment.

Nevertheless, broker clients who are limited to receiving biased recommendations will rationally prefer biased recommendations to no recommendations whenever:

$$E[U_i(Y, Y_{Biased})] - E[U_i(Y, N)] > 0.$$

This comparison depends crucially on how client *i* would have invested in the absence of broker recommendations $E[U_i(Y,N)]$. Everything else equal, the lower the expected utility associated with client *i*'s counterfactual portfolio, the more likely that 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). Furthermore, the cost and quality of recommendations that clients receive from their brokers may respond endogenously to the quality of the counterfactual portfolio. For example, the broker fee in Gennaioli et al.'s (2015) model is set to split the gain from trade. The worse the client's counterfactual portfolio, the larger the gain from trade, and the higher the broker fee.

Lacking direct measures of expected utility, we test for differences in portfolio characteristics that most plausibly impact expected utility. In our framework, the causal effect of broker recommendations on client *i*'s portfolio characteristic Z is given by:

$$E[Z_i|(Y, Y)] - E[Z_i|(Y, N)].$$

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

The existing literature focuses on the quality of broker recommendations, either comparing broker-sold funds to direct-sold funds or broker client portfolios to self-directed investor portfolios.[13] 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

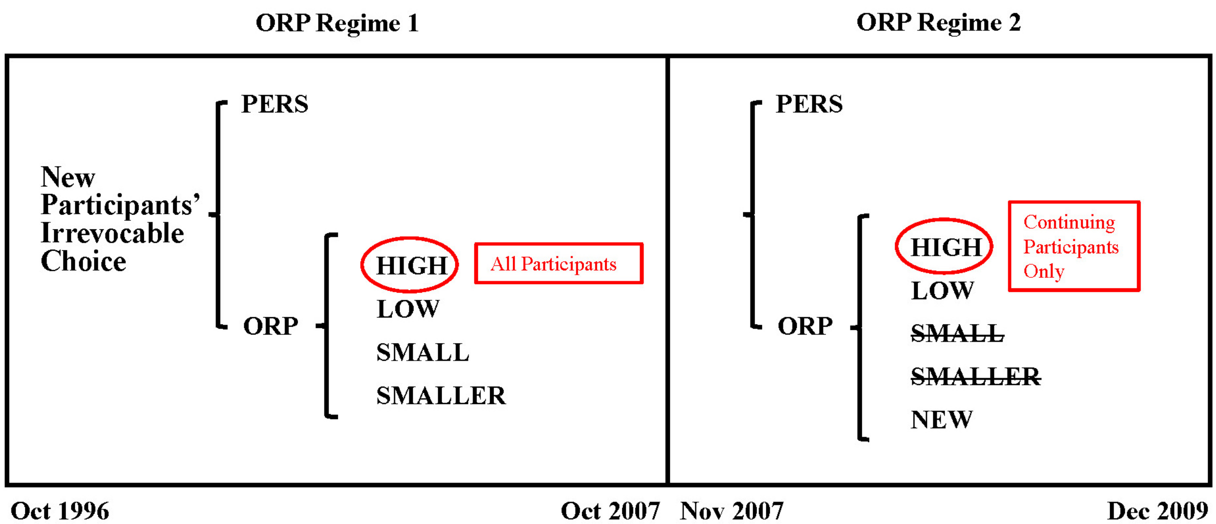
[13] An interesting exception is Bhattacharya et al. (2012), who use an experimental design to estimate the causal effect of offering unbiased recommendations to investors who are not actively seeking them. In our framework, this corresponds to estimating: $E[Z|(No, Yes(Unbiased))] - E[Y|(No, No)]$. 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.

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 of lower average quality than direct-sold funds, and that broker recommendations are conflicted, but they do not shed light on how broker clients would have invested in the absence of broker recommendations.

The other branch of the literature analyzes account-level data, often obtained from non-U.S. based banks. Hackethal, Haliassos, and Jappelli (2012) and Karabulut (2013) use German data to show that broker clients underperform self-directed investors. These comparisons only measure 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 German 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 (2018) compare broker-initiated trades with self-initiated trades at a Swiss bank and find that broker-initiated trades generate higher bank profits. Foerster, Linnainmaa, Melzer, and Previtero (2017) find strong evidence that clients of financial advisors in Canada follow their recommendations but little evidence that a given adviser offers different advice to different clients. Linnainmaa, Melzer, and Previtero (2017) find that financial advisors hold high-cost, actively managed mutual funds in their own portfolios. Moreover, they find that financial advisors would have earned higher after-fee risk-adjusted returns if they had held the average portfolio of their clients—a counterfactual calculation focused on the advisor rather than the client. Finally, Mullainathan, Nöth, and Schoar (2012) use an audit study methodology to measure how recommended portfolios differ from the initial portfolios that the auditors present to the brokers. They find strong evidence that broker recommendations are biased in favor of brokers and little evidence that broker recommendations improve upon the initial portfolios.

While these papers raise important questions about whether and how broker recommendations can be improved, they are largely silent on how actual broker clients would have invested in the absence of these recommendations. In contrast, the evolution of the ORP investment menu allows us to use time-series variation in the access to brokers to identify plausible counterfactual portfolios for investors with the highest predicted demand for broker recommendations.

Figure 2: Oregon University System Retirement Options, 1996-2009



III. Who Seeks Broker Recommendations?

A. Institutional Details

In October 1996, the Oregon University System (OUS) introduced a defined contribution plan, the Optional Retirement Plan (ORP). The goal was to provide a portable alternative to the defined benefit retirement plan being offered to public employees, the Public Employees Retirement System (PERS).[14] 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.[15] 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. We begin by exploiting the fact that, unlike a typical DC retirement plan, ORP participants are allowed to choose from multiple investment providers. Between October 1996 and October 2007, a period which we refer to as "Regime 1," 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*

[14] 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.

[15] 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.

levels of "personal face-to-face service." In contrast, LOW, SMALL and SMALLER are more representative of investor-directed providers available through other DC retirement plans in that they charge lower fees but provide less personalized service.[16] Because the ORP retirement contribution amount is both set by OUS and paid by OUS on behalf of the employee, the scope for brokers to increase savings rates is limited.[17] As a result, broker recommendations in our setting are limited to recommendations on asset allocation and fund selection. The fact that we are studying demand for investment recommendations within a defined contribution retirement plan is likely to explain why we find that demand for financial advice is negatively correlated with proxies for financial literacy (e.g., salary and educational attainment) while papers studying demand for financial advice in other settings tend to find that it is positively correlated.[18]

Effective November 2007, ORP drops HIGH, SMALL, and SMALLER, and adds NEW, a well-known mutual fund family. As a result, ORP participants who join after October 2007 cannot choose to invest their retirement contributions through a broker.[19] We illustrate this timeline in Figure 2. 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.[20] LOW 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 the next most popular, and is chosen by 31.7% of participants. During "Regime 2," the period beginning in November 2007 and ending in December 2009, new participants are limited to LOW or NEW. Of the 734 participants who join ORP during Regime 2, 54.8% choose LOW and 45.2% choose NEW.

Figure 2 highlights the fact that we are studying a selected sample of participants. The last three columns of Table 1 report the number and fraction of ORP-eligible employees who choose ORP over PERS. While the average fraction of ORP-eligible employees choosing ORP is similar

[16] LOW eventually begin offering investors the opportunity to meet one-on-one with representatives, who can provide participants with investment guidance, but not until 2006, and not in the form of an ongoing relationship with a local representative.

[17] In unreported analysis, we find only modest evidence that brokers increase savings rates; 3.3% of ORP participants who invest through HIGH open a supplemental 403(b) retirement plan versus 1.8% of ORP participants who invest through LOW.

[18] For example, Robb, Babiarz, and Woodyard (2012) analyze the 2009 National Financial Capability Study, commissioned by the FINRA Investor Education Foundation. They find that demand for advice on savings, investments, and tax planning is increasing in income and education, while demand for debt counseling is decreasing in income.

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

[20] 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.

during Regime 1 and Regime 2 (24.3% versus 21.0%), there is significant time-series variation in demand for ORP during Regime 1. When we benchmark demand for ORP during Regime 2 with demand during the last 22 months of Regime 1, we find that it decreases from 29.0% of ORP-eligible participants to 21.0%. The most likely explanation is that the lack of access to brokers and extreme market volatility during Regime 2 combined to increase the relative attractiveness of PERS, which insulates employees from market risk. In Section III.E., we describe the steps taken to address possible concerns about changing selection into ORP.

B. Participant Characteristics and the Choice of Investment Provider

Investors may seek broker recommendations because they lack financial knowledge and confidence or because they derive utility from a one-on-one relationship with a broker. An expanding literature links differences in gender, age, income, ethnicity, and education to differences in financial literacy.[21] However, because the ORP is only available to employees of the Oregon University System, our sample of DC plan participants have higher income and education levels than the general population.

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 during Regime 1 is between participants who choose to invest through HIGH (column (2)) and those who choose to invest through LOW, SMALL, or SMALLER (column (3)). These data allow us to estimate 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 the participants who choose one of these two providers. We use job classification codes to identify research faculty (i.e., the 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., the organizational description includes a reference to business, computer sciences, engineering, life sciences, mathematics, physical sciences, or social sciences). Data on educational attainment at the time of employment is collected by a subset of campuses until December 2004 and is available for 57.6%

[21] See Lusardi and Mitchell (2014) for a recent summary of this literature.

of ORP participants.

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 ($3,844 versus $4,511). Second, demand for HIGH is substantially higher in the under-30 age group (21.2% versus 15.6%), which likely includes those 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.[22] 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. However, a comparison of columns (1) and (6) reveals that participants joining during Regime 2 have higher (nominal) salaries, are more likely to be female, and are less likely to be faculty members than those joining during Regime 1. The differences between Regimes 1 and 2 are smaller—but qualitatively similar—when we compare participants joining at the end of Regime 1 to those joining during Regime 2. The slightly higher income levels and slightly higher fraction of participants from business and economics departments suggest slightly higher levels of financial literacy in Regime 2. We account for these differences when using the portfolio choices of ORP participants who join during Regime 2 to identify the counterfactual portfolios of broker clients who join during Regime 1. Because we lack data on educational attainment for participants in Regime 2, we can neither observe nor control for differences in education. However, because the fraction of faculty members joining during Regime 2 is lower than during Regime 1 (45.0% versus 49.5%), the fraction of participants with PhDs is also likely to be lower, suggesting slightly lower levels of financial literacy.

[22] Income and education are well accepted proxies for financial literacy. For example, Alexander, Jones, and Nigro (2008) show that financial literacy is higher for college graduates, people who work at financial institutions, and people earning more than $75,000 per year. Similarly, 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.

C. Predicting Demand for Broker Recommendations

To identify investor characteristics that predict demand for brokers during Regime 1, we estimate a series of probit regressions. 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 3 reports coefficients estimated on the sample of ORP participants described in column (1) of Table 2. In columns (2) and (3), we restrict the sample to participants for whom we observe the date of the initial ORP contribution. In columns (4) and (5), we further restrict our sample to those campuses and years for which data on educational attainment are available. Columns (3) and (5) include a fixed effect for the date of the choice, allowing us to control for the impact of any time-varying economic conditions on demand for brokers. We report marginal effects above standard errors that are clustered on the date of the choice.

The marginal effects in Table 3 are largely consistent with the univariate comparisons in Table 2. Given that one-third of ORP participants choose to invest through HIGH, they are also economically significant. Decreasing an employee's monthly salary by one standard deviation increases 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 than employees in the other age categories. 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 participants for whom we observe educational attainment, we find female participants are approximately 5 percentage points less likely to invest through a broker. With respect to self-reported ethnicity, many of the estimated coefficients are economically large and positive (relative to the omitted category "White"), but only the variable indicating whether the participant self identifies as Asian is statistically significant. The estimated coefficients on participant characteristics are similar with and without the date of choice fixed effects.

The campus fixed effects consistently imply that demand for HIGH is significantly lower at Oregon State University, the Office of the Chancellor, and at Southern Oregon University relative to the University of Oregon, which is the omitted campus. The lower demand for brokers at Oregon State University, which houses the engineering school, is consistent with 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 brokers assigned to each campus.

Overall, the types of participants who choose a broker in our sample are consistent with prior findings in the financial literacy literature. 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 terms of explanatory power, when we focus on predicted values from column (2), we find that 39.2% of Regime 1 participants with predicted demand in the top quartile choose to invest through HIGH versus 14.8% of those in the bottom quartile.[23] In later sections, we use these predicted values to predict demand for default investment options in Regime 2 and to explain variation in portfolio risk taking and returns. In the next section, we use survey evidence to shed additional light on the demand for broker recommendations.

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 intended to measure participant satisfaction with existing plan design and to solicit feedback on potential changes, we were permitted to add questions related to demand for brokers, financial literacy, and risk aversion. Of the 1,380 (38.5%) completed survey responses, 980 are from ORP participants who chose either HIGH (313) or one of the other providers (667) during Regime 1. These survey responses provide us with another opportunity to analyze why some investors choose to invest through a broker and others do not. The important caveat is that we are using survey responses from April 2012 to learn about one-time choices made as early as October 1996.

Panel A of Table 4 reinforces the idea investors choose HIGH when they lack the confidence to invest on their own. Investors who originally chose HIGH (between 1996 and 2007) are significantly more likely to have "an ongoing relationship with a financial advisor" in 2012 (58.7%

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[23] When we focus on the predicted values from column (4), which includes measures of educational attainment, we find that 49.7% of Regime 1 participants with top-quartile predicted demand for HIGH choose to invest through HIGH versus 14.7% of those in the bottom quartile. However, the lack of administrative data on educational attainment during Regime 2 prevents us from using this more-powerful model to identify Regime 2 participants with the high predicted demand for broker recommendations.

versus 36.6%; 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 advisor" (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 advisor" (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 than other investors to implement advice within two weeks (43.4% versus 27.1%) and less likely to ignore advice (8.2% versus 15.2%). Interestingly, only 23.1% of HIGH investors agree or strongly agree with the statement "I understand how much money my advisor earns on my account." Panel C reinforces the (not surprising) idea that investors invest through brokers because they value their recommendations. We also find that HIGH brokers provide "peace of mind" to their clients, 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 advisor," "The number of equity fund choices available," "The level of fund expenses," and "Historical investment performance." Consistent with earlier answers, participants 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 menus available through HIGH and LOW in the Appendix B.) 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.

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), plus an additional question on compounding. For each participant, we calculate the fraction of correct answers. While Lusardi and Mitchell find that only 34.3% of respondents are able to correctly answer all three of their questions, the fraction is significantly higher among our sample of younger, more highly educated investors: 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, this variation is not well captured by the answers to these standard financial literacy questions. Finally, to measure risk aversion, we include a question from the HRS that asks individuals to choose between "Job 1" (which guarantees their current total lifetime income) and "Job 2" (which is equally likely to cause their total lifetime income to go up by x% or to go down by y%). We find that HIGH investors are less likely to prefer "Job 2" across all three scenarios, suggesting that they are more risk averse, on average, than other investors. However, none of the differences are statistically significant at conventional levels.

E. Selection into ORP

The fact that we are studying investors who actively choose a defined contribution retirement plan over a defined benefit retirement plan raises two possible concerns about sample selection. The first is that those OUS employees with the lowest levels of financial literacy and the least investment experience will choose PERS over ORP, resulting in a relatively sophisticated sample of broker clients. Indeed, when Brown and Weisbenner (2007) study the choice between DB and DC retirement plans in the State Retirement System of Illinois, they find that participants with greater levels of financial sophistication are significantly more likely to choose the DC option. We come to a similar conclusion when, in Appendix C, we use participant characteristics to predict demand for PERS versus ORP. This selection may explain why 91.9% of all Regime 1 ORP participants were able to successfully answer all four financial literacy questions. Ultimately, this is a concern about external validity, which we return to in the conclusion.

The second concern is that OUS employees selecting ORP during Regime 2 differ systematically from those selecting ORP during Regime 1. Recall that we use the portfolio choices of Regime 2 participants with high predicted demand for brokers to identify the counterfactual portfolios of broker clients who join during Regime 1. If PERS becomes differentially more attractive during Regime 2 to employees with lower levels of financial literacy, then the sample of investors who join ORP during Regime 2 will be more financially literate than those who join during Regime 1, resulting in fewer reluctantly self-directed investors. The main way that we address this concern is to define reluctantly self-directed investors as those with top-quartile predicted demand for HIGH based on cutoffs defined using the *full sample* of Regime 1 and Regime 2 participants.

Based on this approach, we classify 20.0% of Regime 2 participants as reluctantly self-directed (versus 26.5% of Regime 1 participants). In addition, in Appendix C, we compare the survey responses of ORP participants who join during the end of Regime 1 to those who join during Regime 2. While we find some evidence that Regime 2 participants may be (slightly) less risk averse than their End of Regime 1 peers, we find no difference in the ability to answer the four financial literacy questions. Across all survey questions, the only statistically significant difference is that Regime 2 participants are slightly less likely to rate "Historical investment performance" as "Important" or "Very Important" (74.1% versus 82.5%; p-value of 0.043). To the extent that this difference reflects an increase in average investment experience or financial knowledge among Regime 2 participants (beyond what is captured by the standard financial literacy questions), it reinforces the need to identify ORP participants with top-quartile predicted demand for HIGH using cutoffs based on the full sample.

IV. Default Investments as Substitutes for Broker Recommendations?

We present evidence in this section to answer one of our central questions. Namely, what are the counterfactual portfolios of participants who desire advice in the absence of brokers? We hypothesize that removing access to brokers' recommendations from the 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 investment option is a TDF.

OUS provided us with account-level data from HIGH, LOW, and NEW. A 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. (We describe the data in more detail in Section V.A.) To allow for the possibility that it takes investors several months to actively choose investments, for both HIGH and LOW, we focus on participant *i*'s contribution five months after the initial contribution. For NEW, which only provides data on quarterly account balances, we focus on participant *i*'s holdings in the second quarterly statement.

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.

Because Regime 1 is significantly longer than Regime 2, we also include statistics for participants joining ORP between January 2006 and October 2007 (i.e., the "End of Regime 1"). 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 Fidelity TDF with the target retirement date chosen based on the participant's age. We focus on the sample of participants for which we possess the administrative data required to estimate the demand-for-advice model in column (2) of Table 3, regardless of when the participant joined ORP.[24]

The fraction of participants who remain invested in the default option increases sharply after HIGH is removed from the set of providers, from 15.5% during the end of Regime 1 to 44.2% during Regime 2. This increase is broadly consistent with our hypothesis that default options and broker recommendations are substitutes, as is the fact that most of the demand for default options during Regime 1 comes from LOW. The fraction of broker clients who remain fully invested in the default option during Regime 1 never exceeds 2.0%. In contrast, most of the demand for default options during Regime 2 comes from NEW; 65.2% of the participants who choose to invest through NEW also choose to remain fully invested in the Fidelity TDF. The strong demand for TDFs during Regime 2 is broadly consistent with our hypothesis that TDFs are substitutes for broker recommendations.[25]

Table 6 provides more 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 ("Pr(High)") and then regress demand for the default investment option on these predicted values.[26] 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. Columns (1) and (2) show that demand for the default option during Regime 1 is unrelated

[24] Findings are similar when we focus on the full sample of participants. See Table A4.

[25] Table 5 reveals that demand for LOW's default investment option increases significantly between Regime 1 and Regime 2 (12.6% versus 21.7%). This difference raises the possibility that some of the participants who previously would have chosen to invest through HIGH choose LOW during Regime 2 but lack the confidence to allocate their retirement contributions to non-default investment options. Or, because Regime 2 includes the onset of the financial crisis, the increased demand for LOW's money market fund could reflect a response to declining equity market values. Reassuringly, we find little difference in the demand for LOW's default investment option when we compare the end of Regime 1 to Regime 2 (21.9% versus 21.7%).

[26] 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 not to include a fixed effect for the date of the choice.

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.

In contrast, in Regime 2, when brokers are no longer available, we find that demand for defaults is strongly related to predicted demand for brokers. Pooling participants who choose LOW or NEW, in columns (3) and (4), we find that investors with Pr(HIGH) in the top quartile are 19.2 percentage points (12.1 minus -7.1) more likely to demand the default investment option than those with Pr(HIGH) in the bottom quartile. This difference is statistically significant at the 1-percent level. However, because this specification treats demand for LOW's default money market fund (which is a questionable substitute for broker recommendations) 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, in columns (5) and (6), 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. These findings are consistent with those in Mitchell and Utkus (2012), who conclude that demand for TDFs reflects an underlying demand for investment advice in 401(k) plans that do not offer access to brokers. More importantly, to the extent that reluctantly self-directed investors invest 100% of their retirement contributions in TDFs when brokers are not available, TDFs are the likely counterfactual portfolio for these clients, thereby allowing us to measure the causal impact of broker recommendations by comparing actual broker client portfolios to counterfactual portfolios based on TDFs.

When we limit the sample to participants who choose to invest through LOW, in columns (7) and (8), we do not find that predicted demand for brokers predicts demand for the default money market fund. This finding is also important because it argues against the possibility (also explored in Section V.C) that some reluctantly self-directed participants respond to the lack of broker recommendations during Regime 2 by investing in money market funds.

V. Measuring Causal Effects of Broker Recommendations on Broker Client Portfolios

To measure the causal impact of broker recommendations on their client portfolios we require data from Regime 1 on both the actual and counterfactual portfolios of ORP participants who choose to invest through HIGH. We also require data from Regime 2 on the actual portfolios of ORP participants with high predicted demand for HIGH. To test the risk-taking hypothesis of Gennaioli et al. (2015), we require data from Regime 1 on the actual portfolios of ORP participants who choose to invest through HIGH and LOW.

A. Measuring Portfolio Risk and Return

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. Our 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 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, beginning December 1998 and ending December 2009. The annual account balance data from LOW limits several of our tests. Most notably, it leads us to focus on differences in annual after-fee returns. Finally, NEW provided us with data on quarterly portfolio holdings, beginning in December 2007 (shortly after it was introduced as a provider) and ending in December 2009.

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 and a six-factor model that extends the Carhart (1997) model by adding 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 a TDF, we assume that her target retirement date is the year in which she turns 65. We are primarily interested in comparing actual and counterfactual portfolios for participations who chose to invest through HIGH during Regime 1 or have high predicted demand for investing through a broker. Because Fidelity had the largest market share among TDF providers at the beginning of our sample period (Balduzzi and Reuter (2018)), we restrict the counterfactual investment options to Fidelity Freedom funds. (These are also the TDFs offered through NEW.) 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.[27] 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.

The Sharpe ratio of participant i's actual portfolio in year t is calculated as the average monthly return of the actual portfolio in excess of the risk-free rate of return, scaled by the standard deviation of the excess monthly returns. The Sharpe ratio of participant i's counterfactual portfolio in year t is calculated similarly.

B. Comparing Actual Portfolios of Broker Clients to Counterfactual Portfolios Based on TDFs

Our first empirical strategy for measuring the causal effect of broker recommendations is to compare actual investor portfolios to age-matched counterfactual portfolios based on Fidelity TDFs. Table 7 reports annual summary statistics for actual investor portfolios and counterfactual portfolios based on TDFs. Panel A reveals that broker clients earned annual after-fee returns during

[27] In earlier versions, 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.

our sample period that were 2.98% lower than they would have earned investing in age-matched TDFs (1.85% versus 4.83%). Approximately one-third of this difference in raw returns 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 charged by the underlying investments.[28] 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. These comparisons suggest that brokers significantly increase annual fees, significantly decrease annual after-fee returns, and slightly increase portfolio risk relative to the counterfactual portfolios.[29,30]

We formalize these comparisons in Table 8, where the set of independent variables is expanded to include six-factor alphas and Sharpe ratios. 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 within a particular sample of investors. To allow for correlations in participant *i*'s annual portfolio returns across years and in annual portfolio returns across participants in year *t*, we two-way cluster standard errors on participant *i* and calendar year *t*. Panel A confirms that broker clients earn lower annual after-fee 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 (-0.0491; 5-percent level). But, we cannot reject the hypothesis that

[28] The fees that we label as broker fees are technically "mortality and risk expense charges." According to the SEC webpage describing variable annuities: "Profit from the mortality and expense risk charge is sometimes used to pay the insurer's costs of selling the variable annuity, such as a commission paid to your financial professional for selling the variable annuity to you" (http://www.sec.gov/investor/pubs/varannty.htm). To isolate variation in commissions, our preferred specifications in Appendix D focus on variation in fees across funds with the same investment objective.
[29] Panel B, included for completeness, reveals that self-directed investor earn lower annual after-fee returns than age-matched TDFs, but the level of underperformance is 1.65% per year instead of 2.98% per year. 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 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 in LOW.
[30] Differences between actual portfolios and age-matched TDF portfolios are similar, in Appendix Table A5, when we limit the sample of ORP participants to those for whom we can predict Pr(HIGH).

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

Of course, we are particularly interested in the subset of ORP participants who invest through HIGH during Regime 1 and have top-quartile predicted demand for brokers, because these are the participants for whom TDFs and broker recommendations are likely to be the strongest substitutes. Panel C focuses on this sample of participants. While the estimated difference in annual after-fee returns declines slightly, so does the estimated difference in CAPM betas. Estimated differences in six-factor alphas are slightly more negative than in the full sample of HIGH participants, while estimated differences in Sharpe ratios are slightly less negative. The findings are similar in Appendix Table A6, when we focus on the subset of HIGH participants who stated on the OUS survey that "Access to face to face meetings with a financial adviser" was a very important when choosing between ORP providers. Therefore, for HIGH participants with the highest predicted and stated demand for broker recommendations, switching to these likely counterfactual portfolios would have increased after-fee risk-adjusted performance without significantly altering exposure to market risk. Our estimates imply that this sample of participants would have benefitted from ORP eliminating access to brokers and introducing TDFs before 2009.

Note that when we apply the same empirical strategy to self-directed investors, in Panel D, 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 fact that approximately 10% of LOW portfolios remain invested in the default money market fund. Point estimates suggest that self-directed investors also underperformed age-matched TDFs by economically significant margins, but the differences are not statistically significant at conventional levels. Moreover, these comparisons lack a causal interpretation.

C. Comparing Portfolios of Participants with High Predicted Demand for Brokers Who Join Around Regime Change

Our empirical strategy in the previous section measured the causal effect of broker recommendations on client portfolios for those participants for whom TDFs and brokers are substitutes. However, even among participants with high predicted demand for broker recommendations, some choose to invest through LOW, or to invest through NEW but not invest in a TDF. Arguably, some of these participants may have been harmed by the lack of access to brokers. Therefore, our second empirical strategy compares the portfolios of all participants with high predicted demand for broker recommendations who joined before and after the regime change in November 2007, without conditioning on how they choose to invest.

In Table 9, we limit the sample to participants who joined ORP between January 2006 and December 2008, and for whom Pr(HIGH) is in the top quartile. As discussed above, to address concerns about changes in investor characteristics during Regime 2, we identify the cutoff for the top quartile using the full sample of participants. As a result, we classify 20.0% (not 25.0%) of Regime 2 participants as reluctantly self-directed. Panel A focuses on participants who joined during the end of Regime 1 and Panel B focuses on those who joined during the beginning of Regime 2. We report the fraction of participants that invest through each provider, the fraction who invest 100% in the default option (calculated the same way as in Table 5), and several portfolio-level characteristics for calendar year 2009 calculated using portfolio holdings on December 31, 2008.[31] We focus on the CAPM beta and Sharpe ratio of each participant's portfolio. We calculate averages and standard deviations across participants who join during the same regime or who choose the same provider during the same regime.

During Regime 1, 39.5% of the participants with high predicted demand for brokers choose to invest through a broker, 17.5% (29.0% of 60.5%) choose to invest 100% in LOW's money market fund, and the remaining 43.0% choose to allocate their contributions across other funds on LOW's investment menu. During Regime 2, 42.6% (57.4% of 74.3%) of the participants with high predicted demand for brokers choose to invest 100% in a TDF, 9.8% (23.1% of 42.6%) choose to invest 100% in LOW's money market fund, and the remaining 52.5% choose to allocate their contributions across other funds on NEW's or LOW's investment menus.

These patterns reveal that observed participant demand for brokers in Regime 1 is similar to observed participant demand for TDFs in Regime 2 (39.5% versus 42.6%). They also reveal that demand for the money market fund declines during the beginning of Regime 2. Given that those joining during Regime 2 lack access to broker recommendations, we might have expected to find higher demand for the money market fund among the sample of Regime 2 investors with the highest predicted demand for brokers.

When we compare the characteristics of participant portfolios in 2009, we find no evidence that investors with high predicted demand for broker recommendations are worse off in Regime 2.

[31] Our decision to compare portfolio characteristics in 2009 is driven by the very small number of new participants through December 2007 (see Table 1) and the lack of comprehensive return data for HIGH's menu after 2009.

For those joining during Regime 2, CAPM betas are significantly higher (0.76 versus 0.59; difference significant at the 1-percent level), and Sharpe ratios are significantly higher (0.40 versus 0.30; difference significant at the 5-percent level). Finally, while the across-participant standard deviations of CAPM beta are similar, the standard deviations of Sharpe ratios are significantly lower in Regime 2 (0.06 versus 0.38).[32] Therefore, in our setting, in which advice is limited to asset allocation and fund selection and participants have access to TDFs, we conclude that conflicted advice is dominated by no advice.

D. Differences in Risk and Return with Brokers

In Table 10, we use a third empirical strategy to estimate the causal impact of broker recommendations on client portfolios. Specifically, we compare the portfolios of broker clients and self-directed investors who are both predicted to invest through HIGH. We measure the average difference in risk or return between HIGH and LOW by including 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 invest through HIGH hold systematically different portfolios relative to investors who are predicted to rely upon a broker but invest through LOW. 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, participant i's portfolio choices are likely to be highly correlated across years, and portfolio returns will be highly correlated across participants investing during the same year, we again cluster standard errors on both participant i and calendar year t.

We find that predicted demand for brokers has opposite effects on risk taking in the two samples of investors. In column (3), when the probability of choosing HIGH equals 0.391 (the cutoff for top-quartile demand), investing through a broker is predicted to increase the CAPM beta by 0.117 while investing through HIGH is predicted to decrease the CAPM beta by 0.083. The

[32] When we re-calculate statistics for portfolios during Regime 2 excluding participants that invest in TDFs, we find the mean CAPM beta is 0.61, the standard deviation of the CAPM beta is 0.36, the mean Sharpe ratio is 0.38, and the standard deviation of the Sharpe ratio is 0.07.

difference of 0.200 is both economically and statistically significant. When we shift our focus to the volatility of monthly returns, in column (2), the findings are qualitatively similar. Higher predicted values are associated with greater volatility when the participant relies on broker recommendations and lower volatility when they do not. To the extent that investors with high predicted demand for brokers investing through LOW have made a mistake, we can use these estimates to learn about the causal effect of brokers in an institutional setting that lacks TDFs. One interpretation for the differences in risk-taking is that brokers tilt their clients towards riskier investments with the goal of masking underperformance due to broker fees. Another interpretation, consistent with the predictions of Gennaioli, Shleifer, and Vishny (2015), is that brokers help investors with lower levels of financial sophistication (or less trust in financial markets) to bear market risk. The fact that broker client portfolios have CAPM betas that are economically and statistically indistinguishable from the CAPM betas of age-matched TDFs supports the risk bearing interpretation.

In Appendix Table A7, 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 10 with interaction terms based on this measure instead of Pr(HIGH). The benefit is a less noisy measure of demand for brokers. The cost is a greatly reduced sample size (4,581 participant-years in column (1) of Appendix Table A7 versus 11,528 in column (1) of Table 10. The findings are qualitatively similar. Plan participants who desire 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.

This final empirical strategy highlights the crucial role that plan design plays in determining an investor's counterfactual portfolio. When brokers are available and TDFs are not, the relevant counterfactual portfolio for investors with high predicted demand for face-to-face advice may be a money market fund or other investment option with lower-than-optimal exposure to market risk. More generally, in settings without default options, it may be impossible to identify how broker clients would have invested in the absence of broker recommendations.

VI. 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 characteristics 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. Doing so allows us to make three contributions to the literature on financial advice.

First, we highlight the need to benchmark actual broker client portfolios against counterfactual portfolios constructed without access to brokers. Second, by showing that demand for broker recommendations within our setting is driven by demand for advice on asset allocation and fund selection, we challenge the common implicit assumption that it is appropriate to use low-cost index funds or the actual portfolios of self-directed investors as proxies for the counterfactual portfolios of broker clients. Benchmarking actual client portfolios against low-cost index funds is likely to be even less informative in samples of investors with lower levels of financial literacy than we observe in our highly-educated sample.

Third, and most importantly, we benchmark actual client portfolios against plausible counterfactual portfolios. Doing so reveals that the answer to "Is Conflicted Investment Advice Better than No Advice?" depends on the institutional setting. Our first two empirical strategies, which lead us to conclude that the answer is no, rely on the fact that ORP introduced TDFs at the same time that it eliminated access to broker recommendations. Our third empirical strategy, on the other hand, highlights a potentially positive impact of broker recommendations on client portfolio risk levels in institutional settings that lack well-designed defaults investment options, such as TDFs. Had the ORP simply eliminated access to broker recommendations without introducing TDF defaults, we likely would have observed much lower levels of portfolio risk among some of the reluctantly self-directed investors. In other words, broker recommendations may plausibly be needed to increase risk taking by investors operating outside of defined contribution retirement plans with well-designed defaults. Moreover, outside of retirement accounts, the advice to save more or buy life insurance may plausibly benefit both brokers and their clients. Within defined contribution retirement plans, however, we find that plan participants seeking investment advice can achieve similar exposure to market risk at lower cost through the use of TDFs.

References

Alexander, Gordon J., Jonathan D. Jones, and Peter J. Nigro, 1998, "Mutual Fund Shareholders: Characteristics, Investor Knowledge, and Sources of Information," *Financial Services Review* 7, 301–316.

Anagol, Santosh, Shawn Cole, and Shayak Sarkar, 2016, "Understanding the Incentives of Commissions Motivated Agents: Theory and Evidence from the Indian Life Insurance Market," *Review of Economics and Statistics* 99(1), 1−15.

Balduzzi, Pierluigi, and Jonathan Reuter, 2018, "Heterogeneity in Target-Date Funds: Strategic Risk-taking or Risk Matching?" *Review of Financial Studies* (Forthcoming).

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.

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.

Berk, Jonathan, and Richard Green, 2004, "Mutual Fund Flows and Performance in Rational Markets," *Journal of Political Economy* 111, 1269–1295.

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, *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, 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, 2017, "Retail Financial Advice: Does One Size Fit All?" *Journal of Finance* 72(4), 1441–1482.

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

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.

Hackethal, Andreas, Roman Inderst, and Steffen Meyer, 2012, "Trading on Advice," working paper.

Hoechle, Daniel, Stefan Ruenzi, Nic Schaub, and Markus Schmid, 2018, "Financial Advice and Bank Profits," *The Review of Financial Studies*, 31, 11, 4447-4492.

Hung, Angela A. and Joanne K. Yoong, 2013, "Asking for Help: Survey and Experimental 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.

Karabulut, Yigitcan, 2013, "Financial Advice: An Improvement for Worse?" working paper.

Linnainmaa, Juhani T., Brian T. Melzer, and Alessandro Previtero, 2017, "The Misguided Beliefs of Financial Advisors," Working Paper.

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 Olivia Mitchell, 2007b, "Financial Literacy and Retirement Preparedness: Evidence and Implications for Financial Education Programs," Working Paper.
Lusardi, Annamaria, and Olivia Mitchell, 2014, "The Economic Importance of Financial Literacy: Theory and Evidence," *Journal of Economic Literature* 52, 5–44.

Lusardi, Annamaria, and Peter Tufano, 2009, "Debt Literacy, Financial Experiences and Overindebtedness," 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.

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

Robb, Cliff, Patryk Babiarz, and Ann Woodyard, 2012, "The Demand for Financial Professionals' Advice: The role of Financial Knowledge, Satisfaction, and Confidence," *Financial Service Review* 21, 291–305.

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.

Von Gaudecker, Hans-Martin, 2015, "How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice?" *Journal of Finance* 70, 489–505.

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	% Actively Choosing ORP over PERS
Regime 1. HIGH is available to new ORP participants									
10/96 - 01/99	No	603	699	274	66		1,642	2,996	35.4%
02/99 - 12/99	Yes	141	169	55	24		389	1,861	17.3%
01/00 - 12/00	Yes	153	192	57	25		427	2,004	17.6%
01/01 - 12/01	Yes	108	204	52	15		379	1,867	16.9%
01/02 - 12/02	Yes	91	229	56	14		390	1,916	16.9%
01/03 - 12/03	Yes	133	275	28	31		467	1,662	21.9%
01/04 - 12/04	Yes	130	244	45	18		437	1,518	22.4%
01/05 - 12/05	Yes	197	294	46	37		574	1,558	26.9%
01/06 - 12/06	Yes	148	285	53	30		516	1,476	25.9%
01/07 - 10/07	Yes	139	355	57	35		586	1,220	32.4%
TOTAL		**1,843**	**2,946**	**723**	**295**		**5,807**	**18,078**	**24.3%**
Regime 2. HIGH is not available to new ORP participants									
11/07 - 12/07	Yes		11			15	26	189	12.1%
01/08 - 12/08	Yes		182			169	351	1,304	21.2%
01/09 - 12/09	Yes		209			148	357	1,261	22.1%
TOTAL			**402**			**332**	**734**	**2,754**	**21.0%**

Note: We use Oregon University System payroll data to identify the investment provider for each new Optional Retirement Plan (ORP) participant. The unit of observation is participant i in the first month that she contributes to her 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 recommendations. 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				End of Regime 1	Regime 2
ORP Participants who choose:	Any Provider	HIGH	Not HIGH	LOW	Any Provider	Any Provider
	(1)	(2)	(3)	(4)	(5)	(6)
Sample Size	4,680	1,544	3,136	2,314	762	614
Monthly Salary (mean)	$4,291	$3,844	$4,511	$4,666	$4,474	$5,235
Monthly Salary (median)	$3,729	$3,399	$3,883	$3,992	$3,713	$4,064
Female	48.6%	50.1%	47.8%	45.9%	53.2%	56.4%
Age < 30	17.5%	21.2%	15.6%	13.3%	21.9%	22.5%
30 <= Age < 40	38.9%	36.1%	40.3%	42.0%	41.9%	42.3%
40 <= Age < 50	28.2%	27.3%	28.7%	29.2%	22.4%	17.8%
50 <= Age	15.4%	15.4%	15.4%	15.6%	13.8%	17.4%
Faculty Member	53.3%	50.8%	54.5%	55.7%	49.5%	45.0%
Business or Economics Department	3.5%	1.7%	4.4%	4.5%	3.3%	5.0%
Other Quantitative Department	18.9%	19.0%	18.8%	17.8%	19.2%	13.0%
Asian	7.6%	7.3%	7.8%	7.6%	10.1%	9.0%
Black	2.6%	2.9%	2.4%	2.7%	2.9%	2.8%
Hispanic	3.4%	3.4%	3.4%	3.7%	4.3%	3.1%
White	84.6%	83.9%	84.9%	84.4%	80.2%	83.6%
Other	1.8%	2.5%	1.5%	1.6%	2.5%	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%		
% missing data	*42.4%*	*42.2%*	*42.4%*	*44.4%*	*100.0%*	*100.0%*

Note: This table describes the sample of ORP participants for whom we observe salary, gender, age, job status, and self-reported ethnicity. We report statistics for: (1) the full sample of participants joining ORP during Regime 1; (2) the sample that chooses HIGH during Regime 1; (3) the sample that chooses LOW, SMALL, or SMALLER during Regime 1; (4) the sample that chooses LOW during Regime 1; (5) the full sample of participants joining ORP at the end of Regime 1; and (6) the full sample of participants joining ORP during Regime 2. Regime 1 begins in October 1996 and ends in October 2007. The End of Regime 1 begins in January 2006 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 that the plan is chosen or in January 1999 (whichever is later). 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, mathematics, 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 Oregon Institute of Technology, Oregon State, Portland State, and University of Oregon, the sample period in columns (4) and (5) end in December 2004, and the sample is limited to participants hired by these campuses. 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, or as quantitative but not business or economics. 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 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?		When you receive investment advice, do you usually implement the advice:			"I understand how much money my adviser earns on my account"	
			LOW	HIGH		
Never	15.0%	"Within two weel	27.1%	43.4%	Strongly Agree	8.0%
Once a year	55.9%	"Within two mont	34.7%	30.9%	Agree	15.1%
Twice a year	21.6%	"Within the year"	23.0%	17.6%	Disagree	50.9%
More than twice	7.5%	"Never"	15.2%	8.2%	Strongly Disagree	25.9%
N	213	N	553	233	N	212

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

"My adviser's expertise in deciding iow much of my investments to pu n the stock market is very valuabl		"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 Disagre	5.3%	Strongly Disagre	6.3%	Strongly Disagre	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 990 participants who chose HIGH (313) or one of the other three providers (677) between October 1996 and October 2007. The survey response rates are similar for the two groups: 17.0% (313/1843) for HIGH and 17.1% (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		End of Regime 1		Regime 2	
Provider	Default	N	Invest 100% in Default?	N	Invest 100% in Default?	N	Invest 100% in Default?
HIGH	Fixed annuity	862	2.0%	172	1.2%		
LOW	Money market fund	1,465	12.6%	384	21.9%	240	21.7%
NEW	Target date fund					256	65.2%
		2,327	8.7%	556	15.5%	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, the table is restricted to participants who originally chose to invest through HIGH, LOW, or NEW. We further restrict the sample 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. We distinguish between Regime 1 (which includes all participants joining before November 2007), end of Regime 1 (which includes only those joining between January 2006 and October 2007), and Regime 2 (which includes all participants joining after October 2007).

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 who join during Regime 1) and participants who do not have access to HIGH (i.e., participants who join during Regime 2). The independent variable of interest in columns (1), (3), (5), and (7) is the predicted probability that participant i chooses HIGH based on the estimated coefficients in Column (2) of Table 3. The independent variables of interest in the remaining columns are dummy variables indicating whether Pr(High) falls into the top or bottom quartile, where these cutoffs are defined using the full sample of Regime 1 and Regime 2 participants. 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 four columns are restricted to the subset of new participants who choose to invest through NEW, which offers TDFs as its default investment option, or LOW, which offers a money market fund 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. All HIGH Participants

	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. All LOW Participants

	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	19.88%	2.88%	0.704	0.00%	25.17%	3.20%	0.709	0.00%
2000	-7.81%	4.19%	0.683	0.00%	-3.15%	4.14%	0.772	0.00%
2001	-10.68%	4.70%	0.728	0.00%	-9.46%	4.50%	0.730	0.00%
2002	-14.39%	3.73%	0.731	0.00%	-14.49%	4.04%	0.702	0.00%
2003	20.02%	1.97%	0.584	0.00%	25.88%	2.40%	0.685	0.00%
2004	8.68%	1.52%	0.567	0.00%	9.83%	2.02%	0.843	0.00%
2005	6.22%	1.50%	0.610	0.00%	8.14%	2.05%	0.793	0.00%
2006	10.93%	1.26%	0.558	0.00%	12.20%	1.87%	0.940	0.00%
2007	8.22%	1.60%	0.618	0.00%	8.86%	2.40%	0.831	0.00%
2008	-22.13%	3.72%	0.539	0.00%	-34.90%	5.95%	0.905	0.00%
2009	15.39%	3.21%	0.534	0.00%	29.80%	5.32%	0.822	0.00%
1999-2009	3.21%	2.56%	0.600	0.00%	4.86%	3.50%	0.818	0.00%

Note: In this table, we summarize the actual and counterfactual portfolios of participants who join during Regime 1 and choose to invest through HIGH or LOW. 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, or 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 realized 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. Comparing Actual Portfolios of Participants Joining During Regime 1 to Target Date Funds, 1999-2009

Dependent:	Annual Portfolio Return	Volatility of Monthly Returns	CAPM Beta	6-Factor Annual Alpha	Difference in Sharpe Ratios
	(1)	(2)	(3)	(4)	(5)
Panel A. All HIGH Participants					
HIGH	-0.0308 ***	0.0054 *	0.0913	-0.0208 **	-0.0491 **
	(0.0116)	(0.0028)	(0.0575)	(0.0105)	(0.0203)
N	5,560	5,560	4,719	3,938	5,560
Panel B. HIGH Participants for which we can predict Pr(HIGH)					
HIGH	-0.0267 **	0.0033	0.0532	-0.0213 **	-0.0476 **
	(0.0118)	(0.0023)	(0.0583)	(0.0104)	(0.0234)
N	2,953	2,953	2,540	2,121	2,953
Panel C. HIGH Participants with Pr(HIGH) in Top Quartile					
HIGH	-0.0240 **	0.0027	0.0359	-0.0228 **	-0.0460 **
	(0.0096)	(0.0018)	(0.0503)	(0.0099)	(0.0206)
N	974	974	828	682	974
Panel D. All LOW Participants					
LOW	-0.0145	-0.0083 ***	-0.1872 ***	-0.0080	0.0082
	(0.0270)	(0.0028)	(0.0430)	(0.0060)	(0.0216)
N	14,422	14,422	14,421	14,363	14,422

Note: The unit of observation is the portfolio of ORP participant i in calendar year t. Although the sample is restricted to participants who join ORP during Regime 1, we analyze annual portfolio characteristics from the full sample period (1999 to 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 holdings on December 31 of the prior year, assuming no additional retirement contributions during year t. Characteristics of TDF portfolios are based on the Fidelity TDF to which we assign participant i. The OLS regressions in Panels A, B, and C test for differences between the actual and TDF portfolios of three samples of HIGH investors. Panel A focuses on the full sample of HIGH participants; Panel B focuses on the subset of HIGH participants for which we estimate Pr(HIGH) using the specification in column (2) of Table 3; Panel C focuses on the subset of HIGH participants with Pr(HIGH) in the top quartile (based on the distribution of Pr(HIGH) across all participants. The OLS regressions in Panel D test for differences between the actual and TDF portfolios of LOW investors. The dependent variable in each regression is the difference between the characteristics of participant i's actual and counterfactual portfolios. Because we are estimating the average value within each population, we do not report R2 (which is mechanically equal to 0.0000). 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. Portfolios Characteristics of High-Broker-Demand Participants Around Regime Change

Provider	Default	% Choosing Option	N Participants	N 100% Default	Invest 100% in Default?	CAPM Beta (2009) Mean	CAPM Beta (2009) Std Dev	Sharpe Ratio (2009) Mean	Sharpe Ratio (2009) Std Dev
Panel A. Participants Joining ORP Between January 2006 and October 2007 (End of Regime 1)									
HIGH	Fixed annuity	39.5%	45	1	2.2%	0.83	0.36	0.17	0.63
LOW	Money market fund	60.5%	69	20	29.0%	0.48	0.33	0.36	0.13
			114	21	18.4%	0.59	0.37	0.30	0.38
Panel B. Participants Joining ORP Between November 2007 and December 2008 (beginning of Regime 2)									
NEW	Target-date fund	57.4%	35	26	74.3%	0.95	0.14	0.43	0.04
LOW	Money market fund	42.6%	26	6	23.1%	0.52	0.36	0.36	0.06
			61	32	52.5%	0.76	0.34	0.40	0.06
	Excluding TDFs				15.4%	0.61	0.36	0.38	0.07
Change between NEW and HIGH					72.1% ***	0.12 *		0.26 **	
Change between Regime 2 and Regime 1					34.0% ***	0.18 ***		0.09 **	

Note: The sample is restricted to participants who joined ORP between January 2006 and December 2008, and for whom the predicted probability of using HIGH is in the top quartile. Panel A focuses on participants who joined during the end of Regime 1 (between January 2006 and October 2007), whereas Panel B focuses on participants who joined during the beginning of Regime 2 (November 2007 through December 2008). We calculate the market share of HIGH versus LOW or NEW versus LOW, the fraction of participants that invest 100% in the default investment option (following the same approach as Table 5), the average CAPM beta based on portfolio holdings at the end of 2008, the standard deviation of CAPM betas across participants, the average Sharpe ratio earned by participants during 2009, the standard deviation of Sharpe ratios across participants. The sample used to calculate the average Sharpe ratio excludes five portfolios that allocate more than 50% to fixed annuities (which have positive excess returns and standard deviations very close to zero). This includes one participant who invests through HIGH and four participants who invest through LOW. In each panel, we report changes in fractions and means. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 10. Portfolio Characteristics and Predicted Demand for Brokers, 1999-2009

Dependent:	Annual Portfolio Return	Volatility of Monthly Returns	CAPM Beta	6-Factor Annual Alpha	Sharpe Ratio
	(1)	(2)	(3)	(4)	(5)
HIGH?	-0.0226	0.0099 ***	0.1408 ***	-0.0084	-0.0716
	(0.0229)	(0.0031)	(0.0468)	(0.0114)	(0.0438)
Pr(HIGH) * HIGH?	0.0201	0.0073 **	0.3000 ***	-0.0176 ***	0.0028
	(0.0132)	(0.0036)	(0.0838)	(0.0064)	(0.0535)
Pr(HIGH) * LOW?	0.0002	-0.0089 ***	-0.2128 ***	-0.0055	0.0105
	(0.0242)	(0.0031)	(0.0623)	(0.0053)	(0.0529)
P-values from test that coefficients are equal on interaction terms	0.5779	0.0010 ***	0.0000 ***	0.0758 *	0.9189
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
N	11,528	11,528	11,115	10,716	11,528
R2	0.8066	0.5349	0.1465	0.2464	0.7316

Note: The unit of observation is the portfolio of ORP participant i in calendar year t. Although the sample is restricted to participants who join ORP during Regime 1, we analyze annual portfolio characteristics from the full sample period (1999 to 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 holdings on December 31 of the prior year, assuming no additional retirement contributions during year t. The dependent variables are 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, and 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 sample and specification in column (2) 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 A1. Overview of Actual Investment Menus

Asset Class	HIGH Beginning Regime 1	HIGH End Regime 1	HIGH End Regime 2	LOW Beginning Regime 1	LOW End Regime 1	LOW End Regime 2	NEW 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
Default option		Fixed Annuity			Money Market		TDF
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 throughout 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 (shortly before the end of Regime 1 in October 2007). NEW offers the same menu throughout Regime 2. Defaults options vary in the cross section but not the time series. The default is a fixed annuity for HIGH, money market fund for LOW, and a target date fund for NEW.

Table A2. Demand for PERS versus ORP

Dependent:	1 if OUS employee chooses PERS					
Date Range:	2/99 - 12/09	2/99 - 12/09	1/06 - 12/09	1/06 - 12/09	2/99 - 12/04	2/99 - 12/04
	(1)	(2)	(3)	(4)	(5)	(6)
ORP Regime 2?	0.0359		0.0441			
	(0.0338)		(0.0449)			
PERS Regime 2?	-0.0644 **				-0.0466	
	(0.0307)				(0.0563)	
Female	-0.0021	-0.0019	-0.0170	-0.0150	-0.0068	-0.0049
	(0.0063)	(0.0063)	(0.0104)	(0.0118)	(0.0106)	(0.0110)
Age [30, 40)	-0.1132 ***	-0.1020 ***	-0.0952 ***	-0.0865 ***	-0.0564 ***	-0.0512 ***
	(0.0131)	(0.0101)	(0.0172)	(0.0138)	(0.0184)	(0.0163)
Age [40, 50)	-0.0635 ***	-0.0582 ***	-0.0357 **	-0.0281 *	0.0008	-0.0013
	(0.0126)	(0.0113)	(0.0182)	(0.0162)	(0.0178)	(0.0178)
Age [50, 100]	0.0296 ***	0.0170	0.0464 ***	0.0330 **	0.1025 ***	0.0824 ***
	(0.0095)	(0.0105)	(0.0174)	(0.0163)	(0.0165)	(0.0171)
Asian	-0.0130	-0.0077	-0.0110	-0.0052	0.0153	0.0132
	(0.0109)	(0.0102)	(0.0211)	(0.0208)	(0.0168)	(0.0162)
Black	-0.0529 ***	-0.0576 ***	-0.0410	-0.0532 *	-0.1020 ***	-0.1057 ***
	(0.0199)	(0.0218)	(0.0352)	(0.0336)	(0.0396)	(0.0447)
Hispanic	0.0392 ***	0.0418 ***	0.0491 **	0.0615 ***	0.0338	0.0238
	(0.0128)	(0.0114)	(0.0211)	(0.0188)	(0.0232)	(0.0225)
Other Ethnicity	0.0283	0.0273	0.0369	0.0198	0.0185	0.0020
	(0.0170)	(0.0165)	(0.0309)	(0.0341)	(0.0308)	(0.0318)
Faculty	-0.0238	-0.0275	0.0132	-0.0057	0.0433 *	0.0323
	(0.0223)	(0.0172)	(0.0352)	(0.0316)	(0.0244)	(0.0222)
Business & Economics	-0.0761 ***	-0.0636 ***	-0.1096 ***	-0.0978 ***	-0.0613 *	-0.0522
	(0.0250)	(0.0230)	(0.0400)	(0.0381)	(0.0393)	(0.0374)
Other Quantitative	-0.0576 ***	-0.0388 ***	-0.0649 ***	-0.0390 ***	-0.0240 *	-0.0186
	(0.0093)	(0.0087)	(0.0181)	(0.0158)	(0.0141)	(0.0146)
PhD					-0.2515 ***	-0.2069 ***
					(0.0320)	(0.0226)
Masters					-0.0395 **	-0.0390 **
					(0.0190)	(0.0164)
Campus: Oregon State	0.0101	0.0172	-0.0483 **	-0.0441 **	0.0501 ***	0.0600 ***
	(0.0125)	(0.0113)	(0.0221)	(0.0219)	(0.0190)	(0.0138)
Campus: Portland State	0.1223 ***	0.1133 ***	0.1327 ***	0.1157 ***	0.1305 ***	0.1275 ***
	(0.0103)	(0.0084)	(0.0195)	(0.0145)	(0.0170)	(0.0152)
Campus: Oregon Inst. of Technology	-0.0034	0.0066	-0.0492	-0.0646 *	0.0387	0.0613 **
	(0.0224)	(0.0180)	(0.0425)	(0.0418)	(0.0337)	(0.0228)
Campus: Eastern Oregon	0.0744 ***	0.0882 ***	0.1201 ***	0.1307 ***		
	(0.0153)	(0.0122)	(0.0255)	(0.0195)		
Campus: Southern Oregon	0.1213 ***	0.1248 ***	0.0732 ***	0.0820 ***		
	(0.0128)	(0.0089)	(0.0229)	(0.0200)		
Campus: Western Oregon	0.0763 ***	0.0861 ***	0.1008 ***	0.1079 ***		
	(0.0140)	(0.0112)	(0.0235)	(0.0205)		
Office of the Chancellor	-0.0870 **	-0.0574	-0.1789 **	-0.1741 *		
	(0.0443)	(0.0426)	(0.0975)	(0.1038)		
Date of choice fixed effects?	---	Yes	---	Yes	---	Yes
N	19,438	19,438	6,174	6,174	6,898	6,898
Pseudo-R2	0.0622	0.1702	0.0670	0.1579	0.0916	0.2257

Note: The Probit specifications in Table A2 are similar to those in Table 3. The dependent variable equals one if OUS employee i chooses PERS as his retirement plan and zero if he chooses ORP. The independent variables are the same as in Table 3, with three exceptions. First, we cannot include monthly salary because we only observe monthly salary for the subset of employees who choose ORP. Second, we include a dummy variable indicating if the choice between PERS and ORP occurs during ORP Regime 2 (i.e., on or after November 2007). Third, we include a dummy variable indicating if the choice between PERS and ORP occurs during PERS Regime 2, when the employer contribution rate for new employees was permanently reduced (i.e., on or after September 2003). Columns (1) and (2) focus on the portion of our sample period for which we observe the date of the choice (i.e., on or after February 1999), columns (3) and (4) are restricted to the last four years of our sample period, and columns (5) and (6) are restricted to the subset of campuses and calendar years for which we observe data on educational attainment. Columns (2), (4), and (6) include date of choice fixed effects. 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 A3. Testing for Differences in Survey Responses between End of Regime 1 and Regime 2

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

	Do you have an ongoing 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
End of Regime 1	225	39.1%	85	36.5%	189	37.6%	52.9%	9.5%
Regime 2	151	36.4%	52	30.8%	123	39.0%	51.2%	9.8%
Difference		-2.7%		-5.7%		1.5%	-1.7%	0.2%
P-value		0.599		0.496		0.796	0.771	0.946

Panel B. 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
End of Regime 1	244	45.9%	242	57.0%	246	72.8%	245	82.5%
Regime 2	163	44.2%	162	54.9%	110	67.9%	162	74.1%
Difference		-1.7%		-2.1%		-4.9%		-8.4%
P-value		0.731		0.679		0.292		0.043

Panel C. 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%
End of Regime 1	207	92.8%	144	28.5%	142	49.3%	158	85.4%
Regime 2	134	92.2%	107	26.2%	105	59.1%	109	85.3%
Difference		-0.6%		-2.3%		9.8%		-0.1%
P-value		0.747		0.686		0.129		0.978

Notes: This table compares the characteristics of ORP participants who join during the end of Regime 1 (between Januaruy 2006 and October 2007) to those of participants who join during Regime 2 (between November 2007 and December 2009). The survey answers summarized in Panels A, B, and C mirror those summarized in Panels A, D, and E of Table 4.

Table A4. Demand for Default Investment Option, by Provider and Regime

Sample period:		Regime 1		End of Regime 1		Regime 2	
Provider	Default	N	Invest 100% in Default?	N	Invest 100% in Default?	N	Invest 100% in Default?
HIGH	Fixed annuity	1,492	2.9%	237	1.7%		
LOW	Money market fund	2,341	9.5%	554	17.7%	256	21.5%
NEW	Target date fund					272	64.0%
		3,833	6.9%	791	12.9%	528	43.4%

Note: Table 5 is restricted to the subsample of new 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. This table does not impose either sample restriction.

Table A5. Comparing Actual Portfolios to Counterfactual Portfolios Based on Target-Date Funds, 1999-2009

Panel A. All HIGH Participants

	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								
2000	-15.51%	6.28%	0.931	0.91%	-4.00%	4.35%	0.812	0.00%
2001	-21.42%	7.89%	1.288	0.93%	-10.83%	4.91%	0.795	0.00%
2002	-19.60%	4.84%	1.118	0.91%	-16.22%	4.44%	0.771	0.00%
2003	25.18%	2.91%	0.793	0.90%	27.81%	2.60%	0.751	0.00%
2004	9.65%	2.29%	0.841	0.89%	10.34%	2.15%	0.903	0.00%
2005	4.69%	2.18%	0.882	0.89%	8.48%	2.17%	0.841	0.00%
2006	10.42%	1.66%	0.809	0.90%	12.69%	1.97%	0.991	0.00%
2007	4.61%	2.38%	0.839	0.84%	9.06%	2.52%	0.875	0.00%
2008	-33.05%	5.91%	0.816	0.83%	-36.18%	6.17%	0.940	0.00%
2009	26.74%	5.42%	0.852	0.84%	30.42%	5.52%	0.854	0.00%
1999-2009	1.24%	3.76%	0.881	0.87%	4.07%	3.59%	0.874	0.00%

Panel B. All LOW Participants

	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								
2000	-8.40%	4.37%	0.697	0.00%	-3.78%	4.30%	0.802	0.00%
2001	-10.66%	4.70%	0.733	0.00%	-10.06%	4.68%	0.759	0.00%
2002	-14.25%	3.69%	0.731	0.00%	-15.41%	4.25%	0.738	0.00%
2003	19.48%	1.90%	0.565	0.00%	26.83%	2.50%	0.718	0.00%
2004	8.56%	1.45%	0.536	0.00%	10.07%	2.08%	0.872	0.00%
2005	6.28%	1.43%	0.581	0.00%	8.32%	2.11%	0.818	0.00%
2006	10.79%	1.20%	0.530	0.00%	12.43%	1.92%	0.965	0.00%
2007	8.16%	1.52%	0.584	0.00%	8.97%	2.46%	0.854	0.00%
2008	-21.15%	3.55%	0.512	0.00%	-35.68%	6.08%	0.926	0.00%
2009	14.36%	3.07%	0.511	0.00%	30.16%	5.44%	0.841	0.00%
1999-2009	3.10%	2.35%	0.559	0.00%	4.50%	3.66%	0.859	0.00%

Note: This table is the same as Table 7 except that the sample of ORP participants is further limited to those for whom we can predict demand for HIGH (column (2) of Table 3). The fact that we do not observe the date of the choice between HIGH and LOW before February 1999 explains why we do not report statistics for 1999.

Table A6. Alternative Version of Table 8 Estimated on Sample of Survey Respondents

Dependent:	Annual Portfolio Return	Volatility of Monthly Returns	CAPM Beta	6-Factor Annual Alpha	Difference in Sharpe Ratios
	(1)	(2)	(3)	(4)	(5)
Panel A. HIGH Participants who responded to survey					
HIGH	-0.0290 ***	0.0041 *	0.0609	-0.0213 **	-0.0488 **
	(0.0102)	(0.0023)	(0.0514)	(0.0101)	(0.0219)
N	1,679	1,679	1,419	1,160	1,679
Panel B. HIGH Participants who responded to survey with highest stated demand for "access to face to face meetings"					
HIGH	-0.0305 ***	0.0039	0.0572	-0.0229 ***	-0.0522 **
	(0.0104)	(0.0024)	(0.0538)	(0.0089)	(0.0219)
N	674	674	571	466	674
Panel C. LOW Participants who responded to survey					
LOW	-0.0161	-0.0072 ***	-0.1619 ***	-0.0089	-0.0050
	(0.0239)	(0.0025)	(0.0398)	(0.0058)	(0.0188)
N	2,902	2,902	2,902	2,895	2,902
Panel D. LOW Participants who responded to survey with highest stated demand for "access to face to face meetings"					
LOW	-0.0167	-0.0076 **	-0.1806 ***	-0.0083	0.0022
	(0.0253)	(0.0031)	(0.0526)	(0.0060)	(0.0235)
N	407	407	407	405	407

Note: In Table A6, the sample is expanded to include all ORP participants regardless of when they chose to join ORP, and then the sample is limited to participants who answered the following survey question: "When choosing between ORP providers assess the importance of the following factors: Access to face to face meetings with a financial adviser". The survey filter explains why the sample sizes are significantly lower than in Table 7. Panel A focuses on the sample of survey respondents who initially chose to invest through HIGH, and Panel B focuses on the subsample with the highest stated demand for "access to face to face meetings". Panels C and D are similar except that they focus on the sample of survey respondents who initially chose to invest through LOW. Because we are estimating the average value within each population, we do not report R2 (which is mechanically equal to 0.0000). 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 two-way 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 A7. Alternative Version of Table 9 Estimated on Sample of Survey Respondents, 1999-2009

Dependent:	Annual Portfolio Return	Volatility of Monthly Returns	CAPM Beta	6-Factor Annual Alpha	Sharpe Ratio
	(1)	(2)	(3)	(4)	(5)
HIGH?	-0.0132	0.0087 ***	0.1337 ***	-0.0087	-0.0266
	(0.0167)	(0.0026)	(0.0397)	(0.0118)	(0.0196)
ORP_FACE * HIGH?	0.0012	0.0002	0.0312	-0.0026	-0.0053
	(0.0018)	(0.0017)	(0.0400)	(0.0019)	(0.0063)
ORP_FACE * LOW?	0.0018	-0.0045 ***	-0.1074 ***	0.0016	0.0276 ***
	(0.0089)	(0.0016)	(0.0347)	(0.0018)	(0.0097)
P-values from test that coefficients are equal on interaction terms	0.9551	0.0432 **	0.0095 ***	0.1532	0.0270 **
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
N	4,581	4,581	4,321	4,062	4,581
R2	0.8468	0.5577	0.1465	0.2277	0.8691

Note: Table A7 differs from Table 10 in two ways. First, as in Table A6, the sample is expanded to include all ORP participants regardless of when they chose to join ORP, and then the sample is limited to participants who answered the following survey question: "When choosing between ORP providers assess the importance of the following factors: Access to face to face meetings with a financial adviser". The survey filter explains why the sample sizes are significantly lower than in Table 9. Second, we interact answers to this question with dummy variables indicating whether the participant invests through HIGH or LOW. ORP_FACE takes on four possible values: 0 ("unimportant"), 0.33 ("somewhat important"), 0.67 ("important"), and 1 ("very important"). 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 two-way 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 A8. Allocation of Retirement Contributions Across Available Funds -- Tobits

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 (e.g., large-cap growth). 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 1.000%. Standard errors are clustered on the date of participant i's contribution. 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. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table A9. Allocation of Retirement Contributions Across Available Funds -- Probits

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	0.229 ***	0.271 ***	0.245 ***	-0.032	-0.027	-0.054
	(0.020)	(0.028)	(0.054)	(0.039)	(0.052)	(0.085)
Not Broker Fee * HIGH	-11.067 ***	-11.417 ***	-16.203 ***	-10.724 ***	-12.851 ***	-18.299 ***
	(0.516)	(0.625)	(2.167)	(0.923)	(0.829)	(2.848)
Broker Fee	20.187 ***	22.582 ***	40.699 ***	23.381 ***	27.456 ***	48.690 ***
	(1.442)	(1.527)	(2.466)	(2.313)	(2.546)	(3.005)
Lagged Return * LOW	0.030	0.487 ***		0.234 ***	0.862 ***	
	(0.037)	(0.174)		(0.076)	(0.106)	
Not Broker Fee * LOW	-9.094	82.574 **		-20.406 ***	-6.630	
	(9.015)	(35.164)		(6.185)	(10.852)	
Ho: Same Sensitivity to Lagged Return?	0.000 ***	0.188		0.001 ***	0.000 ***	
Ho: Same Sensitivity to Not Broker Fee?	0.827	0.007 ***		0.112	0.547	
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	72,392	25,051	61,574	58,840	19,231
Adj. R2	0.1820	0.2050	0.2279	0.1548	0.1775	0.2078

Note: Alternative version of Table A8 that uses Probit regressions to predict whether fund j receives a positive allocation. All variables are scaled so that 1.000 equals 1.000%. Standard errors are clustered on the date of participant i's contribution. 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. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table A10. Allocation of Retirement Contributions Across Available Funds -- OLS

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	0.216 ***	0.269 ***	0.199 ***	-0.023	-0.022	-0.029
	(0.019)	(0.027)	(0.049)	(0.026)	(0.042)	(0.046)
Not Broker Fee * HIGH	-10.219 ***	-8.870 ***	-10.963 ***	-10.321 ***	-9.742 ***	-13.239 ***
	(0.620)	(0.677)	(1.676)	(0.959)	(0.870)	(2.014)
Broker Fee	13.969 ***	14.898 ***	27.838 ***	15.557 ***	16.924 ***	31.479 ***
	(0.942)	(0.923)	(2.466)	(1.317)	(1.321)	(2.483)
Lagged Return * LOW	0.093	1.036 ***		0.392 ***	1.250 ***	
	(0.121)	(0.377)		(0.149)	(0.097)	
Not Broker Fee * LOW	28.243	145.524 **		-20.476 *	-6.700	
	(21.625)	(61.063)		(10.727)	(15.793)	
Ho: Same Sensitivity to Lagged Return?	0.289	0.038 **		0.005 ***	0.000 ***	
Ho: Same Sensitivity to Not Broker Fee?	0.079 *	0.013 **		0.344	0.847	
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	0.1599	0.1945	0.2093	0.1361	0.1752	0.2239

Note: Alternative version of Table A8 that is estimated using linear probability models instead of Probit regressions. All variables are scaled so that 1.000 equals 1.000%. Standard errors are clustered on the date of participant i's contribution. 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. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.