

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

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ABSTRACT

To measure the causal impact of broker recommendations on their clients portfolios, we exploit time-series variation in access to brokers in a defined contribution retirement plan. When brokers are available, we predict demand for brokers using administrative data on plan participants. The observed correlations with age, income, and educational attainment suggest that brokers are chosen by participants who need help with asset allocation and fund selection because they are less financially sophisticated. When brokers are no longer available, we show that demand for default investment options increases differentially among participants with the highest predicted demand for brokers. And, the increases are largest when the default is a target-date fund (TDF), which combines portfolio management with asset allocation. Therefore, we can use portfolios based on TDFs to determine how the broker clients in our setting would have invested in the absence of broker recommendations. We find that actual broker client portfolios earn significantly lower risk-adjusted returns and Sharpe ratios than the counterfactual portfolios—due in part to broker fees that average 0.90% per year—but offer similar levels of systematic risk. When we exploit across-fund variation in the level of broker fees, we find broker clients allocate more dollars to high-fee funds. This finding reinforces the fact that broker clients rely on broker recommendations, and it highlights one potential benefit of replacing brokers with TDFs.

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I. Introduction

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

Before describing our empirical strategy—or the setting that makes it possible—we emphasize the need to identify broker clients’ counterfactual portfolios. Clients benefit from receiving and following broker recommendations when the expected utility of doing so (net of fees) exceeds the expected utility of investing on their own. Everything else equal, this difference in expected utilities depends on the quality of the broker recommendations that they follow. However, broker clients may rationally prefer biased recommendations to no recommendations. This is because the difference in expected utilities also depends on how the clients would have invested in the absence of broker recommendations. The lower the expected utility associated with a client’s counterfactual portfolio, the more likely that the client is to benefit even from biased recommendations—such as to invest in those actively managed mutual funds paying high broker fees. For example, in Gennaioli, Shleifer, and Vishny (2013), brokers increase their clients’ expected utility by increasing equity allocations above counterfactual levels; the high broker fees follow directly from the large gains to trade. On the other hand, the higher the expected utility associated with a client’s counterfactual portfolio, the lower the potential benefit from receiving and following biased (or unbiased) recommendations.

¹ Georgarakos and Inderst (2010) model the impact of financial literacy, trust in financial advice, and legal rights on stock market participation. In their model, demand for financial advice falls with the level of financial literacy.

² Bergstresser, Chalmers, and Tufano (2009) and Del Guercio and Reuter (2013) show that broker-sold mutual funds underperform direct-sold funds.

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

Our empirical setting is the Optional Retirement Plan (ORP), a defined contribution retirement plan introduced by the Oregon University System (OUS) in October 1996, as an alternative to the defined benefit retirement plan covering other state employees.³ When joining ORP, participants choose the investment provider to which their retirement contributions will be sent. Between October 1996 and October 2007, the set of providers includes HIGH, whose network of brokers provide face-to-face recommendations, and three participant-directed options: LOW, SMALL, and SMALLER.⁴ In November 2007, however, HIGH is dropped and new participants are limited to investing through LOW or NEW. Our empirical strategy relies on both the availability of brokers and non-brokers through October 2007 and the loss of brokers beginning in November 2007. OUS helped us to match administrative data on ORP participants with retirement account-level data from HIGH, LOW, and NEW.⁵ Account-level data end in December 2009.

The availability of HIGH until October 2007 allows us to study the demand for brokers within a defined contribution retirement plan. When we focus on demographic characteristics, we find that demand for HIGH is negatively correlated with age, salary, and educational attainment. Demand for HIGH is also significantly lower among participants working within an economics department or business school. These patterns reinforce our prior that ORP participants are more likely to seek broker recommendations when they have lower levels of financial literacy or less investment experience. To provide more direct evidence on the demand for broker recommendations, we administered an online survey to current ORP participants, asking them to weight the factors that led them to choose their initial ORP provider. We find strong evidence that demand for HIGH is driven by demand for face-to-face help with asset allocation decisions.

³ See Chalmers, Johnson, and Reuter (2013) for a description of Oregon's Public Employees Retirement System.

⁴ Benartzi (2001), Benartzi and Thaler (2001), and Agnew et al. (2003) study asset allocation decisions within 401(k) plans, which traditionally have not provided access to financial advisors. Barber and Odean (2000) study the behavior of investors who invest through a discount brokerage, a selected sample of investors who are likely to be the most comfortable making their own investment decisions.

⁵ As we show in Table 1, between October 1996 and October 2006, 82.5% of ORP participants choose to invest through either HIGH or LOW. We lack account-level data for participants who chose to invest through SMALL and SMALLER because these providers were dropped from ORP on November 2007.

These findings imply that the portfolios of broker client reflect the recommendations of their brokers, but they also raise serious questions about the portfolios that these clients would have held in the absence of any recommendations.

The loss of HIGH to participants joining ORP after October 2007 allows us to study the extent to which different default investment options are substitutes for brokers. Using account-level data from HIGH, LOW, and NEW, we identify participants who, after six months, are still allocating 100% of their retirement contribution to the default investment option. Between October 1996 and October 2006, demand for default investment options is low. It ranges from 2.9% for HIGH, where the default is a fixed annuity, to 9.5% for LOW, where it is a money market fund. Between November 2007 and December 2009, when new participants lack access to brokers, demand for default investment options increase significantly. It is 21.5% for LOW, where the default is still a money market fund, and 64.0% for NEW, where the default is a target-date fund (TDF). These changes are broadly consistent with default investments substituting for broker recommendations. To provide more direct evidence on substitution, we show that the model used to predict demand for HIGH in the earlier period successfully predicts demand for the default investment option in the later period.⁶ This is especially true when we focus on the set of participants who invest through NEW, suggesting that TDFs, which make asset allocation decisions for investors, are much closer substitutes for brokers than are money market funds.

Next, we estimate the causal effect of broker recommendations by comparing the actual portfolios of broker clients to counterfactual portfolios based on Fidelity TDFs. We find that broker clients earned significantly lower after-fee returns, lower risk-adjusted returns, and lower Sharpe ratios than they would have earned if they had been defaulted into age-specific Fidelity target-date funds. A significant portion of the underperformance is due to broker fees, which average 90 basis points per year. Point estimates suggest that broker client portfolios are slightly riskier than the counterfactual TDF portfolios, but the differences are not statistically significant at conventional levels.⁷

⁶ Our approach both here and below is related to that in Calvet, Campbell, and Sodini (2009), who combine financial wealth, family size, and educational attainment into a financial sophistication index, and show that higher values of this index are associated with fewer financial mistakes. The mistakes they consider are underdiversification, failure to rebalance, and the disposition effect.

⁷ When we apply the same empirical strategy to self-directed investors, we find that actual portfolio risk is significantly lower than it would have been if self-directed investors had invested in TDFs. These differences partially reflect the finding above that approximately 10% of LOW portfolios remain invested in the default money market fund. Point estimates suggest that self-directed investors underperformed TDFs by economically significant margins, but the differences are not statistically significant at conventional levels.

Gennaioli et al. (2013) motivates another comparison of portfolio risk and returns. Their key prediction, based on the assumption that brokers reduce the disutility associated with bearing financial risk, is that actual portfolios of broker clients will hold more equity than counterfactual portfolios constructed without access to brokers. To test this prediction, we interact the predicted probability that a participant chooses to invest through HIGH with dummy variables indicating whether the participant does or does not invest through HIGH. To the extent that participants who are more comfortable bearing market risk are less likely to invest through a broker, our test will underestimate the impact of brokers on risk taking. Despite this potential bias, the estimated differences in risk taking are striking. Participants who are predicted to invest through a broker and do so hold portfolios with higher total risk (the volatility of monthly return is 1 percentage point higher) and higher systematic risk (the CAPM beta is 0.27 higher) than participants who are predicted to invest through a broker and do not.

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

Our paper contributes to the literature on financial advice in two ways. First, we show that demand for broker recommendations within a defined contribution retirement plan is driven by demand for advice on asset allocation and fund selection. This is not surprising, since the scope for broker recommendations within ORP is limited to asset allocation and fund selection, but it raises the possibility that TDFs are effective substitutes for broker recommendations. Had we been studying demand for recommendations related to taxable investment strategies or estate planning, for example, we likely would have found positive correlations with income, age, and educational attainment, and we would have needed a different strategy to identify investors counterfactual choices. Second, we provide direct evidence that TDFs are effective substitutes for brokers. Our evidence strengthens Mitchell and Utkus' (2012) conclusion that demand for TDFs in 401(k) plans reflects an underlying demand for financial advice. More importantly, it allows us to benchmark the portfolios of broker clients against counterfactual portfolios based on TDFs.

Doing so reveals that broker clients' portfolios offer similar exposure to market risk, but also earn significantly lower after-fee returns and Sharpe ratios. When we compare investors who do and do not use brokers during the first part of our sample period, we find differences in risk taking that are broadly consistent with the prediction of Gennaioli, Shleifer, and Vishny (2013). This suggests that broker recommendations may be needed to increase risk taking by investors operating outside of defined contribution retirement plans. Within defined contribution retirement plans, however, we find that plan participants can achieve similar exposure to market risk at lower cost through the choice of a TDF as the default investment option.

II. Empirical Framework and Literature Review

In this section, we use a simple empirical framework to highlight the challenges that arise when attempting to measure the causal effect of broker recommendations on their clients' portfolios. We also use it to highlight how our paper differs from existing studies of financial advisors. We begin with the observation that investors potentially differ along two dimensions. The first is whether they seek broker recommendations on asset allocation and fund selection. The second is whether they receive and follow these recommendations. We classify investors who seek, receive, and follow recommendations as (Yes, Yes). These investors are broker clients and their portfolios reflect the recommendations of their brokers. We classify investors who seek but neither receive nor follow recommendations as (Yes, No). The portfolios of these reluctantly self-directed investors shed light on how broker clients would have invested in the absence of broker recommendations; the challenge is to identify these investors in real world data. We classify intentionally self-directed investors as (No, No). If intentionally self-directed investors have greater financial knowledge or investment experience than investors seeking broker recommendations, the portfolios of these self-directed investors will be poor proxies for the counterfactual portfolios of broker clients.⁸

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

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

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

⁸ 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.

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

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

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

This is because the difference in expected utilities also depends on how client i would have invested in the absence of broker recommendations. The lower the expected utility associated with client i 's counterfactual portfolio, the more likely he is to benefit even from biased recommendations. For example, investors with lower levels of financial literacy may be both more likely to seek broker recommendations and more susceptible when investing on their own to the forms of strategic complexity described in Gabaix and Laibson (2006) and Carlin (2009). In addition, the lower the expected utility associated with client i 's counterfactual portfolio, the more biased or expensive may be the recommendation that the client receives. For example, the fees charged by brokers in Gennaioli, Shleifer, and Vishny's (2013) model are higher when the expected benefits of broker services to their clients are larger.

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

$$E[Z|\{\text{Yes}, \text{Yes}\}] - E[Z|\{\text{Yes}, \text{No}\}].$$

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

The existing literature focuses on measuring the quality of broker recommendations.⁹ Karabulut and Hackethal (2010) use account level data to show that broker clients underperform self-directed investors. This comparison only measures the causal effect of brokers under the strong assumption that broker clients portfolios would have resembled self-directed investor portfolios in the absence of recommendations. Instead, it is a reasonable way to benchmark the quality of broker recommendations, after adjusting for the fact that some level of underperformance will arise mechanically from the need for clients to compensate their brokers. Bergstress-

⁹ 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: $E[Z|\{\text{No}, \text{Yes}(\text{Unbiased})\}] - E[Z|\{\text{No}, \text{No}\}]$. 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.

er et al. (2009) show that broker-sold mutual funds underperform direct-sold mutual funds after adding back the broker fees, and Del Guercio and Reuter (2013) rationalize this underperformance by showing that flows into broker-sold funds chase raw rather than risk-adjusted returns. Christoffersen et al. (2013) show that flows into broker-sold funds are higher when funds pay higher fees to brokers. Hackethal, Inderst, and Meyer (2012) use portfolio-level data to study trades by broker clients at a German bank. They find that the bank earns higher revenues from the subset of clients who self-report placing the most trust in their brokers. Mullainathan, Nöth, and Schoar (2012) use an audit study methodology to measure how recommended portfolios differ from the initial portfolios that the auditors show to the brokers. They find strong evidence that broker recommendations are biased in directions that are likely to benefit brokers, but find little evidence that broker recommendations improve upon the initial portfolios.

These papers raise important questions about whether and how broker recommendations can be improved, but they are silent on how broker clients would have invested without these recommendations. In this paper, we use time-series variation in the access to brokers to show that TDFs are reasonable counterfactual portfolios for those investors who seek broker recommendations within a defined contribution retirement plan.

III. Who Seeks Broker Recommendations?

A. Institutional Details

In October 1996, OUS introduced a defined contribution plan, known as the Optional Retirement Plan (ORP). The goal was to provide a portable alternative to the defined benefit plan being offered to public employees, known as the Public Employees Retirement System (PERS). 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.¹⁰ New OUS faculty, administrators, and other employees must 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.¹¹ We begin by exploiting the fact that, unlike a typical defined contribution plan, ORP participants are

¹⁰ 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.

¹¹ Chalmers, Johnson, and Reuter (2013) 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.

allowed to choose from among multiple investment providers. Between October 1996 and October 2007, ORP participants have the choice between two insurance companies (which we refer to as HIGH and LOW) and two mutual fund families (SMALL and SMALLER). From our perspective, the most important distinction between the four providers is that HIGH uses—and markets itself as using—a network of brokers to provide relatively *high* levels of “personal face-to-face service.” In contrast, LOW, SMALL and SMALLER are more representative of investor-directed providers available through other defined contribution retirement plans in that they charge lower fees but provide less personalized service.¹² Note that because the ORP retirement contribution amount is set by OUS as a fixed percentage of the employee’s gross salary, and is paid by OUS on behalf of the employee, broker recommendations are limited to asset allocation and fund selection. There is no scope for brokers to increase savings rates within ORP.¹³

To identify how broker clients would have invested in the absence of broker recommendations, we exploit the fact that ORP changes the set of investment providers through the end of our sample period. Effective November 2007, ORP drops HIGH, SMALL, and SMALLER, and adds NEW, a well known mutual fund family. Participants already investing through HIGH are allowed to continue doing so, while participants already investing through SMALL or SMALLER had their investments mapped into comparable funds managed by NEW. Here, the important change is that new ORP participants are restricted to investing through LOW or NEW.

We use administrative data from OUS to identify the provider through which each ORP participant chooses to invest. We report these counts in Table 1.¹⁴ During “Regime 1,” the period between October 1996 and October 2006, LOW is most popular provider. It is chosen by 50.7% of participants. However, HIGH, which offers access to broker recommendations, is also quite popular. It is chosen by 31.7% of participants. During Regime 2, the period beginning in November 2007 and ending in December 2009, when our administrative data from OUS end, new participants are limited to LOW or NEW. LOW is chosen by 54.8% and NEW by 45.2%.

The last two columns of Table 1 report the number of ORP-eligible employees who choose the defined contribution retirement plan, ORP, over the defined benefit retirement plan,

¹² LOW eventually begin offering investors the opportunity to meet one-on-one with representative, who would provide participants with investment guidance, but not until 2006.

¹³ It is possible that brokers increase savings rates outside of ORP. To explore this possibility, we obtained data from OUS on the use of supplementary 403(b) retirement plans by ORP participants. The differences were economically insignificant. Approximately two percent of ORP participants who invest through HIGH open a 403(b) plan versus approximately one percent of all other ORP participants.

¹⁴ 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.

PERS. During Regime 1, 24.3% of ORP-eligible employees choose ORP. During Regime 2, the fraction falls to 21.0%. This decline is smaller than we expected given our prior that the lack of access to brokers combined with negative equity market returns would increase the relative attractiveness of a defined benefit retirement plan (Brown and Weisbenner (2007)). We model the choice between ORP and PERS in the Appendix.

B. Participant Characteristics and the Choice of Investment Provider

Investors may seek broker recommendations because they lack the financial knowledge and confidence required to allocated retirement contributions across asset classes and funds, because they derive utility from the one-on-one relationship, or both. An expanding literature links differences in gender, age, income, ethnicity, and education to differences in financial literacy. However, because ORP is only available to employees of the Oregon University System, our sample of defined contribution plan participants is not representative of the general population. For example, Hispanic women with PhDs may behave differently than the Hispanic women without PhDs who have been studied in many other settings. When interpreting our results, it is important to keep this caveat in mind. Another important caveat is that we are studying the subset of employees who choose a defined contribution plan over a defined benefit plan.

Table 2 reports summary statistics for those OUS employees who choose to join ORP between October 1996 and October 2007. Column (1) corresponds to the full sample of participants for which we observe monthly salary, gender, age, job classification, and self-reported ethnicity. Columns (2) and (3) correspond to the subsamples of participants who do and do not choose HIGH. To the extent that demand for broker recommendations is correlated with demographic characteristics within our sample of investors, we expect to find differences between columns (2) and (3). Because we only possess account-level data for HIGH and LOW, column (4) corresponds to the sample of participants who choose LOW. We use the job classification to identify research faculty (i.e., job classification includes the string “Teach/Res”), participants who are employed by a business school or economics department, and participants who are employed by another “quantitative department” (i.e., organizational description includes a reference to business, computer sciences, engineering, life sciences, mathematics, physical sciences, or social sciences). We only possess data on educational attainment at the time of employment for 58.1% of ORP participants, because these data were only collected by a subset of campuses and only through December 2004.

Univariate comparisons between HIGH and the other providers (or LOW) reveal interest-

ing differences. First, HIGH participants earn significantly monthly salaries are 14.1% lower than other ORP participants. Second, demand for HIGH is substantially higher in the under-30 age group (20.0% versus 15.5%), which likely includes participants with both the longest investment horizons and the least investment experience. Third, demand for HIGH decreases with educational attainment. Of those choosing HIGH, 40.7% have a Ph.D. versus 53.1% 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.¹⁵ 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.

C. Predicting Demand for Broker Recommendations

We estimate a series of probits, in Table 3, to identify those investors characteristics that predict demand for broker recommendations. The dependent variable is one if participant i 's initial ORP retirement contribution is directed to HIGH and zero otherwise. Column (1) of Table 3 reports estimated coefficients estimated on the full sample of ORP participants described in Column (1) of Table 2. This sample includes participants for whom we do not observe the date of the choice (because choices made before February 1999 are coded as January 1999), and it includes participants for whom we do not observe educational attainment. In Columns (2) and (3) of Table 3, we restrict the sample to participants for whom the date of the initial ORP contribution is not left censored at January 1999. This allows us to control directly for time-varying economic conditions (Column (2)), or to include a separate fixed effect for the year and month of the choice (Column (3)). Finally, in Column (4), we further restrict our sample to those campuses and years for which data on educational attainment are available. We report marginal effects, along with standard errors clustered on the month of the choice.¹⁶

The marginal effects in Table 3 are largely consistent with the univariate comparisons. Given the fact that one-third of ORP participants choose to invest through HIGH, they are also economically significant. Increasing an employee's monthly salary by one standard deviation

¹⁵ Income and education are well accepted proxies for financial literacy. For example, Campbell (2006) shows that homeowners with higher income and more education are more likely to refinance their mortgage when interest rates fall. Lusardi and Tufano (2009) provide a comprehensive overview of the literature on financial literacy and retirement behavior.

¹⁶ Since choices made before February 1999 are coded as January 1999, and these choices are included in the sample used to estimate coefficients in Column (1), in this sample, we allow for clustering in all of the early choices.

reduces demand for a broker by approximately seven percentage points. Similarly, employees who are less than 30 years old when hired (the omitted category) are approximately seven percentage points more likely to invest through a broker. Participants with PhDs are approximately 11 percentage points less likely to invest through a broker, and those employed by a business school or economics department are an additional 10-18 percentage points less likely to invest through a broker. The one notable difference between Table 2 and Table 3 is that when we restrict the sample to those participants for which we observe data on educational attainment, we find female participants are approximately 5 percentage points less likely to invest through a broker. With respect to ethnicity, many of the estimated coefficients are positive and economically significant (relative to the omitted category “White”), but only the dummy variable indicating whether participant i reports being Asian is statistically significant.

To explore the impact of recent equity market movements on the demand for a broker, in Column (2), we control for the return on the S&P 500 index over the prior 12 months and for the value of the Chicago Board Options Exchange Market Volatility Index (VIX) at the beginning of the month.¹⁷ Our prediction is that demand for brokers will be higher when recent equity market returns have been lower or more volatile because investors will be more sensitive to downside risk. However, we find no support for either prediction. When we instead control for variation in market conditions by including a separate fixed effect for the year and month of the choice, the estimated coefficients on participant characteristics are quantitatively similar.

When we turn our attention to the campus fixed effects, we find that demand for HIGH is significantly lower at Oregon State University, the Office of the Chancellor, and the three regional campuses than at University of Oregon (the omitted category). The lower demand for brokers at Oregon State University, which houses the engineering school, is consistent with the evidence that numeracy is an important determinant of financial literacy (Lusardi and Mitchell (2007a)). Another explanation—more likely to apply to the three regional campuses—is that across-campus differences in demand for HIGH reflect variation in the quality or accessibility of the broker(s) assigned to each campus.

In summary, our evidence on which participants choose HIGH is largely consistent with the existing literature on financial literacy. Older, more highly educated, and more highly paid employees are more likely to be financially literate and less likely to value investment recom-

¹⁷ Chalmers and Reuter (2012) find that payout choices by PERS retirees respond to both measures.

mendations from brokers. The lower demand for brokers by employees of business schools and economics departments lends further support to this interpretation. In the next section, we use survey evidence to shed additional light on the demand for broker recommendations. In later sections, motivated by the approach in Calvet, Campbell, and Sodini (2009), we use the predicted values from the probits estimated in Table 3 to predict demand for default investment options and variation in portfolio risk taking and returns.

D. Survey Evidence on the Demand for HIGH versus LOW

OUS emailed a survey to the 3,588 current participants of the Optional Retirement Plan in April 2012. While the survey was primarily intended to measure participant satisfaction with existing plan design and to solicit feedback on several potential changes, we were permitted to add several questions related to the use of brokers, financial literacy, and risk aversion. Of the 1,380 (38%) completed survey responses, 791 are from ORP participants who chose either HIGH (297) or LOW (494) during our sample period. The survey responses for these investors provide a window into the minds of investors who faced the choice between different investment providers. (The fact that the survey did not require completion of all questions explains the variation in sample size from question to question.) The obvious caveat is that we are asking participants to recall how they made decisions as far back as October 1996.

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

Panel B reveals that 84.9% of HIGH investors meet with a broker at least once a year. It also reveals that those investing through HIGH are more likely to implement advice quickly (43.4% versus 24.6%) and less likely to ignore advice (8.2% versus 17.0%) than those investing through LOW. Interestingly, only 23.3% of HIGH investors agree or strongly agree with the statement “I understand how much money my adviser earns on my account.” Panel C reinforces the idea that HIGH investors seek investment advice. Consistent with the prediction in Gennaio-

li, Shleifer, and Vishny (2013), it also reveals that HIGH investors seek “peace of mind” from an advisor that they can trust.

Panel D describes the weights that ORP participants place on investment provider characteristics. Investors who originally chose HIGH place significantly more weight on “Access to face-to-face meetings with a financial adviser” when choosing between investment providers. While 39.3% of LOW investors rate face-to-face meetings as important or very important, the fraction is 69.9% of HIGH investors (p-value of 0.000). (Investors who chose HIGH were asked to evaluate the statement “meeting with my broker gives me peace of mind.” Within this sample, 76.8% choose agree or strongly agree.)

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 driven by demand for the larger menu. For example, in October 1996, HIGH offers access to 40 different investments—four times the number of investments available through LOW. (We summarize the investment options available through HIGH and LOW in the Appendix.) While slightly more HIGH investors rate “The number of equity fund choices available” as important or very important (57.4% versus 55.7%; p-value of 0.653), the difference is neither economically large nor statistically significant. The fact that HIGH investors place slightly less weight on recent fund returns when choosing between providers (80.8% versus 87.3%; p-value of 0.015) is interesting in light of the evidence in Table 9 that they are more likely to chase recent returns when choosing which funds to invest in.

Finally, Panel E reveals only modest differences in risk aversion and financial literacy. To measure risk aversion, we include a question from “HRS 2006 – Module 2” of the Health and Retirement Survey (HRS) that asks individuals to choose between “Job 1” (which guarantees them their current total lifetime income) and “Job 2” (which is equally likely to cause their total lifetime income to go up by x% or to go down by y%). We find no statistically significant evidence that LOW investors are more risk averse than HIGH investors. To measure financial literacy we include three questions that Lusardi and Mitchell (2006) created for the HRS (on compounding, inflation, and the risk associated with investing in a single stock versus a stock mutual fund), plus an additional question on compounding. For each participant, we calculate the fraction of correct answers. While Lusardi and Mitchell (2006) find that only one-third of respondents were able to correctly answer all three of their questions, the fraction is significantly higher among our sample of younger, more highly educated investors. Specifically, 90.0% of HIGH

investors answered all four questions correctly versus 93.3% of LOW investors. While the 3.3% difference is statistically significant at the 5-percent level (p-value of 0.034), it is not economically large. In other words, to the extent that demand for investment recommendations is driven by variation in financial literacy, that variation does not captured by answers to standard financial literacy questions.

IV. Default Investments As Substitutes For Broker Recommendations?

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

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

Table 5 summarizes demand for default investment options during Regime 1, when HIGH and LOW are available, and Regime 2, when LOW and NEW are available. Note that the default investment option differs across the three providers. For HIGH, it is a fixed annuity; for LOW, it is a money market fund; and for NEW, it is a TDF with the target retirement date cho-

sen based on the participant's age.¹⁸ Panel A focuses on the full sample of ORP participants, Panel B focuses on the sample of participants for which we possess the administrative data required to estimate the model in Column (1) of Table 3 (regardless of whether the participant joined ORP during Regime 1 or Regime 2), and Panel C focuses on the slightly smaller sample for which we also observe the date of the choice. The fraction of participants who demand the default option varies across these three samples of participants, but only slightly.

Table 5 reveals several interesting patterns. First, the fraction of participants that remain invested in the default increases sharply after HIGH is dropped from the set of providers, from less than 10% in Regime 1 to more than 40% in Regime 2. Second, during Regime 1, the fraction of broker clients that remain invested in the default option is less than 3%. Third, approximately 65% of the participants who choose to invest through NEW remain invested in the TDF. The strong demand for TDFs in Regime 2 is consistent with our hypothesis that TDFs are de facto substitutes for broker recommendations. Finally, demand for LOW's default investment option also doubles between Regime 1 and Regime 2, from 11% to 22%. This may reflect the fact that some of the participants who previously would have chosen to invest through HIGH choose LOW but lack the confidence to allocate their retirement contributions to non-default investment options. Or, because Regime 2 includes the onset of the recent financial crisis, the increased demand for LOW's money market funds may reflect a conscious response to declining equity market values.

Table 6 provides direct evidence on the extent to which default investments are substitutes for broker recommendations. We regress demand for the default investment option on the predicted demand for brokers based on the estimated coefficients in Column (3) of Table 3.¹⁹ We include a separate fixed effect for the year and month of the choice, to control for average changes in the demand for defaults based on changes in market conditions, and we cluster standard errors on this date. We find that demand for the default during Regime 1 is unrelated to predicted demand for brokers. This likely reflects the fact that investors who are the least confidence picking their own funds self-select into HIGH, where brokers then actively recommend other investments. On the other hand, we find that demand for defaults is strongly related to predicted demand for brokers during Regime 2, when brokers are no longer available.

¹⁸ OUS' decision to limit the set of providers in 2007 was a response to the Pension Protection Act of 2006, which effectively encouraged firms to offer TDFs as default investment options (Balduzzi and Reuter (2013)).

¹⁹ Findings are similar when we use predicted values from Column (1), which allows us to include participants for whom the date of the choice is not observed, but prevents us from include a fixed effect for the date of the choice.

Pooling participants who choose LOW or NEW, we find that investors whose predicted values are in the top tercile are 17.7 percentage points more likely to demand the default investment option than investors whose predicted values are in the bottom tercile, a difference that is statistically significant at the 5-percent level. This specification treats demand for LOW's default money market fund the same as demand for NEW's default TDF. When we limit our sample to participants who chose to invest through NEW, we find an even stronger positive relation between demand for the default and predicted demand for brokers (coefficient on Pr(HIGH) increases from 0.521 to 0.747). Now, demand for TDFs by investors in the top tercile of predicted demand for brokers is 25.3 percentage points higher than by investors in the bottom tercile, and this difference is statistically significant at the 1-percent level. Mitchell and Utkus (2012) study fund selection in a large number of 401(k) plans that do not offer access to brokers and conclude that demand for TDFs reflects an underlying demand for investment advice. Our findings in columns (5) and (6) strengthen their conclusion. More importantly, because we find many potential broker clients invest 100% of their retirement contributions in TDFs when brokers are not available, we are able to use counterfactual portfolios based on TDFs to measure the causal impact of broker recommendations on their clients portfolios.²⁰ We do so in the next section.

V. Causal Effect of Broker Recommendations on Broker Client Portfolios

A. Testing for Differences in Risk and Return

To measure the causal impact of broker recommendations on their client portfolios we require data on both the actual and counterfactual portfolios of ORP participants who choose to invest through HIGH. To test the risk-taking hypothesis of Gennaioli et al. (2013), we require data on the actual portfolios of ORP participants who choose to invest through LOW.

We combine the participant-level administrative data from OUS with two types of participant-level data from HIGH and LOW. First, we observe how each participant's monthly ORP contribution is allocated across the available investment vehicles. The monthly contribution data from HIGH begin in October 1996, when ORP is introduced, and ends in December 2009. However, the monthly contribution data from LOW does not begin until December 1997. Since we infer enrollment dates from the date of the first monthly retirement contribution, enrollment

²⁰ Had OUS not replaced HIGH with a provider offering a TDF as its default, we could still have measured the causal impact of broker recommendations by focusing on the sample of ORP participants predicted to use a broker then comparing the actual portfolios of participants joining during Regime 1 with the actual portfolios of participants joining during Regime 2.

dates for ORP participants investing through LOW are left censored at December 1997. Therefore, we limit any test that depends on date on the choice, such as tests for return chasing in the initial choice of investments, to the period January 1998 through December 2009. Second, we observe how much each participant has invested in each investment vehicle. The account balance data from HIGH is monthly; it begins in October 1996 and ends in December 2009. However, the account balance data from LOW is annual; it begins in December 1998 and ends in December 2009. The lack of monthly account balance data from LOW limits several of our tests. Most significantly, it forces us to focus on differences in annual after-fee returns.

To calculate the actual annual after-fee return of participant i in year t , we combine data on participant i 's dollar holdings of each investment option at the beginning of year t with data on the after-fee returns earned by each investment option during year t . Our sample of annual returns begins with 1999 (because account balance data from LOW begin in December 1998) and ends with 2009. To calculate participant i 's exposure to a risk factor in year t , we weight the estimated factor loading of investment j at the beginning of year t by the fraction of her portfolio allocated to investment j at the beginning of year t . For investment j in year t , we estimate factor loadings using the prior 24 monthly returns. We consider a one-factor model based on CAPM, a four-factor model based on Carhart (1997), and a six-factor model that adds the excess return on the MSCI Barra EAFE index, to capture exposure to international equity, and adds 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 off the expected return on each factor, obtained by multiplying each portfolio's estimated factor loading at the beginning of year t by the return of the factor during year t . To calculate the volatility of monthly returns, we calculate changes in monthly account balances.

To determine participant i 's counterfactual allocation to TDFs, we assume that her target retirement date is the year in which she turns 65. Because Fidelity had the largest market share among TDF providers at the beginning of our sample period (Balduzzi and Reuter (2013)), we restrict the counterfactual investment options to Fidelity Freedom funds. When the target retirement year is less than or equal to 2010, we allocate 100% of her portfolio to the Fidelity Freedom 2010 fund. When the target retirement year is greater than or equal to 2040, we allocate 100% of her portfolio to the Fidelity Freedom 2040 fund. For target retirement years between

2011 and 2039, we pick the single TDF with the closest target retirement date.²¹ We then use monthly fund-level data from Fidelity to calculate annual risk-adjusted returns and the volatility of monthly returns. Because allocations to TDFs are determined entirely by investor age, variation in counterfactual portfolios across HIGH (and LOW) investors is driven by variation in the distribution of investor ages.

Table 7 compares actual investor portfolios to counterfactual portfolios based on TDFs. Panel A reveals that broker clients earned annual after-fee returns during our sample period that were 2.98% lower than they would have earned investing in TDFs (1.84% versus 4.82%). Approximately one-third of this difference can be explained by the fact that TDFs are less expensive than brokers. Broker clients in ORP pay average annual broker fees of 0.90% on top of the management and administrative fees and charged by the underlying investments. Broker clients' portfolios also exhibit more risk taking than the counterfactual portfolios, with larger differences when we focus on the volatility of monthly returns (3.82% versus 3.39%) than when we focus on CAPM beta (0.853 versus 0.797). The size of these differences varies over time, helping to explain the difference in returns. Specifically, the counterfactual portfolios benefit from fact that TDFs offered investors lower exposure to market risk during the start of our sample period and higher exposure to market risk during the end. As a result, the average annual after-fee return earned by TDFs exceeded the average annual after-fee return earned by actual broker client portfolios in nine of the eleven years. Expressed as a fraction of investor-year observations, TDFs outperform actual broker client portfolios 71.0% of the time. These comparisons imply that brokers significantly increased annual fees, significantly decreased annual after-fee returns, and slightly increased risk taking relative to the counterfactual portfolios.

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

²¹ In earlier drafts, we assigned portfolio assets to the Fidelity Freedom fund(s) with the target retirement date(s) closest to the participant's target retirement date. For example, when the target retirement date was 2029, we allocated 10% of the portfolio to the Fidelity Freedom 2020 fund and 90% to the Fidelity Freedom 2030 fund. Our findings were quantitatively similar.

default investment option. Although we might expect some self-directed investors to replace their actual portfolios with TDFs following the introduction of TDFs to ORP, the comparisons in Panel B lack any sort of causal interpretation.

It follows from the comparisons above that broker clients underperform self-director investors by 1.28% per year. This is partially due to the average annual fees of 0.90% that broker clients pay to their brokers. However, the average difference masks significant time-series variation in relative performance. HIGH investors earn significantly higher average after-fee returns when U.S. equity markets post strong positive returns (1999, 2003, and 2009) and significantly lower annual after-fee returns when U.S. equity markets post strong negative returns (2000, 2001, 2002, and 2008). These patterns reinforce the conclusion that broker clients bear significantly more risk than self-directed investors. One interpretation is that brokers recommend greater-than-optimal levels of risk, perhaps because more volatile returns make it harder for their clients to detect underperformance. In terms of the average level of systematic risk, however, broker client portfolios resemble TDF portfolios. Another interpretation, in the spirit of Genaioli et al. (2013), is that self-directed investors hold lower-than-optimal levels of risk. We explore this possibility in Table 8.

Panel A tests for differences in the characteristics of actual and counterfactual portfolios. The set of characteristics is expanded to include six-factor alphas and Sharpe ratios. The odd-numbered columns are limited to the sample of broker clients and the even-numbered columns are limited to the sample of self-directed investors. In each case, we regress the characteristic of participant i 's actual portfolio minus the characteristic of his counterfactual portfolio on a constant, which measures the average difference. To allow for correlations both in annual portfolio returns across participants in year t and in participant i 's annual portfolio returns across years, we cluster standard errors on year t and participant i . The findings are broadly consistent with Table 7. Namely, 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 (-0.1436; 5-percent level).²² But, we cannot reject the hypothesis that the actual and counterfactual portfolios have the same levels of systematic risk (and total risk).

In Panel B, we use a different empirical strategy to estimate the causal impact of broker

²² In Panel A, the Sharpe ratio is defined as the average difference in monthly returns of the actual and counterfactual portfolios, scaled by the standard deviation of the difference in monthly returns. In Panel B, the Sharpe ratio is defined as the average monthly return of the actual portfolio minus the risk-free rate of return, scaled by the standard deviation of the excess monthly return.

recommendations. The odd-numbered columns test for differences between the actual portfolios of broker clients to the actual portfolios of self-directed investor, including a separate fixed effect for each calendar year. In other words, these columns essentially repeat the comparisons from Table 7. While the point estimates suggest that broker clients underperform by economically significant amounts, none of the performance differences is statistically significant. However, the estimated differences in risk taking are both economically and statistically significant.

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

We find that predicted demand for brokers has opposite effects on risk taking in the two samples of investors. In column (6), a one standard deviation increase in the probability of choosing HIGH is predicted to increase the CAPM beta of broker clients by 0.160 *but* decrease the CAPM beta of self-directed investors by 0.108—a economically and statistically significant difference of 0.268. When we shift our focus to the volatility of monthly returns, in column (4), the findings are qualitatively similar. Higher predicted values are associated with greater volatility when the participant invests through HIGH and lower volatility when he does not. These differences are consistent with brokers tilting their clients toward higher beta investments to more readily mask underperformance, but also with Gennaioli, Shleifer, and Vishny's (2012) prediction that brokers reduce the disutility associated with bearing financial risk. Regardless, Mitchell

and Utkus' (2012) finding that the introduction of TDFs into 401(k) retirement accounts increases equity exposure the most for those workers aged 34 and younger suggests that TDFs are a less expensive way to increase risk-taking by less experienced investors.

B. Comparing the Investment Selection of HIGH and LOW Investors

To implement an asset allocation plan, an investor must allocate her monthly retirement contributions across an appropriate set of funds. In Table 9, we explore the impact of brokers on fund selection. We test two hypotheses. The first concerns return chasing. Within the full universe of mutual funds, there is strong evidence that the relation between inflows and performance is convex, with the best performing mutual funds receiving a disproportionate share of the dollars.²³ At the same time, because studies like Carhart (1997) find little evidence that abnormal returns persist, investors should not allow recent returns to distort their asset allocation decisions. Therefore, we test whether return-chasing behavior differs between broker clients and self-directed investors. To the extent that brokers discourage return chasing, we expect to find less evidence of return chasing by broker clients. The implicit assumption underlying this comparison is that broker clients would have been at least as likely to engage in return chasing without a broker. An alternative test is whether broker clients exhibit any return chasing at all since there can be no return chasing in a portfolio that allocates 100% to a single TDF.

The second hypothesis concerns the agency conflict that can arise when financially unsophisticated (or trusting) investors seek investment recommendations from financially sophisticated intermediaries. We also use across-fund variation in broker fees in the HIGH investment menu to test whether HIGH clients are more likely to allocate their retirement dollars to investments paying higher broker fees. Here, our research question most closely matches that of Christoffersen et al. (2013), who find that cross-sectional variation in the level of broker fees helps to explain cross-sectional variation in mutual fund flows, and Hackethal, Inderst, and Meyer (2012), who find that broker recommendations respond to sales incentives.

The dependent variable in Table 9 is the fraction of participant i 's retirement contribution that is allocated to fund j in month t . Because this variable is nonnegative, estimation is via Tobit. The sample consists of all ORP participants for whom the enrollment date is uncensored, and all of the funds available to HIGH or LOW investors in month t . To focus attention on active fund choices, we exclude those participants who invest solely in the default option. There

²³ See, for example, Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998), and Del Guercio and Tkac (2002).

are three independent variables of interest. To test for return chasing, we include the net return on fund j over the prior twelve months interacted with dummy variables that indicate whether participant i invests through HIGH or LOW. To test for possible agency conflicts, we include the fee that fund j pays each year to the broker. For HIGH investments, the broker fee is a constant 55, 85 or 105 basis points; for LOW investments, the broker fee is zero. To test whether investors are sensitive to the level of fund fees more broadly, we include the annual fees charged by the fund that are not paid to the broker (i.e., the total annual fee minus the broker fee). Interacting “Not Broker Fee” with dummy variables indicating whether the fund is available to HIGH or LOW investors allows us to test whether brokers steer investors away from fees from which the brokers do not benefit. We control for the fund’s broad asset category and lagged factor loadings and for the full set of participant-level controls from Table 3 (although findings are unchanged when we exclude fund-level controls, participant-level controls, or both sets of controls). Because we are testing for differential sensitivities to lagged returns and fees across ORP providers, we also include a separate fixed effect for each provider each month, so that we are comparing fund returns and fees within each menu relative to the other funds within the same menu. Standard errors are clustered on date.

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

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

fit the brokers.

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

IV. Conclusion

We use unique investor-level data from the Oregon University System to estimate the causal impact of financial advisors on their clients' portfolios. Our starting point is the observation that the net benefit of broker recommendations depends on both the quality of the recommendations and the quality of the counterfactual portfolio. We have three main findings. First, we document significant differences between those investors who choose to invest through brokers and those who do not. Employees choosing to invest through a broker are younger, less highly educated, and less highly paid. They are also more likely to state that they chose HIGH to meet face-to-face with a broker, and that they relied upon their broker's recommendations when deciding how to invest. Demand for HIGH does not appear to be driven by differences in risk aversion.

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

Third, when we benchmark broker client portfolios against counterfactual portfolios based on TDFs, we find that broker recommendations lead to higher annual fees (due in part to average annual broker fees of 0.90%), lower risk-adjusted returns, and lower Sharpe ratios., but

similar levels of exposure to market risk. In other words, within the context of a retirement plan with a default investment option, choosing TDFs as the default can decrease annual fees without decreasing risk taking. When we compare the outcomes of investors with high predicted demand for broker recommendations during Regime 1, before TDFs are available, we find that broker clients have much higher levels of exposure to market risk. These findings are consistent with the predictions of Gennaioli et al. (2012), suggesting that brokers may add more value in settings that lack a sensible default investment option.

Although our estimates come from a single DC retirement plan, they should be of broader interest. DC retirement plans place important investment decisions in the hands of individuals, many of whom possess limited financial knowledge (e.g., Lusardi and Mitchell (2006)). One approach to improving the quality of individual investment decisions is to invest in educational programs that increase financial literacy (e.g., Bernheim, Garrett, and Maki (2001) and Xu and Zia (2012)). Another approach is to shift investment decisions back onto employers through the use of default investments, such as TDFs (e.g., Balduzzi and Reuter (2012) and Mitchell and Utkus (2012)). A third approach is to have employers provide individuals with access to financial advice via financial intermediaries. Our main conclusion is that a well-chosen default investment option can dominate access to broker recommendations, at least with respect to the characteristics of retirement plan portfolios. To the extent that investors derive utility from face-to-face meetings with brokers that they do not derive from TDFs, this utility needs to be weighed against the higher fees and potential for biased recommendations.

Appendix A. Financial Advice versus Financial Guidance

The Employee Retirement Income Security Act (ERISA) prohibits defined contribution pension plan providers from giving their own financial advice on the investment options within their plans.²⁴ To comply with ERISA, HIGH uses algorithms developed by Ibbotson Associates to generate financial advice for investors with managed accounts. However, OUS prohibits HIGH from directly managing the “participant-directed” accounts of ORP investors. Because of this restriction, it is more accurate to say that HIGH provides ORP participants with face-to-face access to financial guidance.

Fortunately, within the context of a fixed investment menu, the distinction between financial guidance and financial advice is small. ERISA defines financial advice narrowly, as a recommendation that is immediately actionable. Under this definition, the recommendation to “invest 100% of your retirement assets in Vanguard’s S&P 500 index fund” is *financial advice*. In contrast, the recommendation to “invest 100% of your retirement assets in a low-cost S&P 500 index fund” is *financial guidance* because the recommendation is personalized but not immediately actionable. This remains true even if the investment menu offers a single S&P 500 index fund. Therefore, while brokers employed by HIGH are prohibited from offering financial advice, they are allowed to offer financial guidance (and education)—a distinction that is likely lost on those seeking relationships with brokers.²⁵

²⁴ DOL Advisory Opinion 2001-09A, also known as the The SunAmerica Opinion Letter, permits defined contribution retirement plan providers to offer financial advice only when they outsource asset allocation and investment selection decisions to independent, third party providers.

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

Appendix B. Overview of the HIGH and LOW Investment Menus

ORP participants face different investment menus when they invest through HIGH and LOW. In Table A2, we report the number of investment options in each asset class at the beginning and end of our sample period. We also report the number of investment options that are actively managed versus passively managed, and the number of investment options that advised by the provider versus outside asset management firms (for example, HIGH provides access to the HIGH Small-Cap Value Fund, which is advised by HIGH, and the SIT Mid-Cap Growth Fund, which is advised by SIT). There are several notable differences between the two investment menus. First, HIGH offers four-times as many investment options as LOW in October 1996 (40 versus 10). Even after LOW increases its investment menu in July 2007, HIGH still offers more than three-times as many investment options (61 versus 19). Second, HIGH's investment menu is skewed toward domestic equity, offering investments with narrow investment mandates (such as Small-Cap Value or Mid-Cap Growth). Third, HIGH does not offer any exposure to real estate. Fourth, while HIGH's investment menu grows significantly over our sample period, access to investments advised by other firms declines significantly. For example, HIGH introduces its own Mid-Cap Growth Fund in September 1998 and drops the SIT Mid-Cap Growth Fund in May 2006. Finally, as we discuss above, the two providers have different default investments. The default in LOW is a money market, while the default in HIGH is a fixed annuity. However, it is an open question which if any of the differences in investment menus influenced the choice of ORP provider. In Table A3, we summarize the information about investment provider menus that OUS provided to new employees in 2002. This information understated the differences in the sizes of the investment menus.

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

Date Range	Observe Date of Choice?	HIGH	LOW	SMALL	SMALLER	NEW	ORP	PERS
Regime 1. HIGH is available to new ORP participants								
10/96 - 01/99	No	603	699	274	66		1,642	2,996
02/99 - 12/99	Yes	141	169	55	24		389	1,864
01/00 - 12/00	Yes	153	192	57	25		427	2,004
01/01 - 12/01	Yes	108	204	52	15		379	1,869
01/02 - 12/02	Yes	91	229	56	14		390	1,915
01/03 - 12/03	Yes	133	275	28	31		467	1,663
01/04 - 12/04	Yes	130	244	45	18		437	1,517
01/05 - 12/05	Yes	197	294	46	37		574	1,557
01/06 - 12/06	Yes	148	285	53	30		516	1,476
01/07 - 10/07	Yes	139	355	57	35		586	1,222
TOTAL		1,843	2,946	723	295		5,807	18,083
Regime 2. HIGH is not available to new ORP participants								
11/07 - 12/08	Yes		193			184	377	1,493
01/09 - 12/09	Yes		209			148	357	1,261
TOTAL			402			332	734	2,754

Note: We use Oregon University System payroll data to identify the provider to which new Optional Retirement Plan (ORP) participants direct their retirement contributions. The unit of observation is participant i in the first month that she contributes to her 401(a) ORP account. Between October 1996 and October 2007, participants have the choice of four providers: SMALL, SMALLER, LOW, and HIGH. Notably, HIGH markets itself as providing personal face-to-face service. Because OUS payroll data begin in January 1999, initial contribution dates before February 1999 are left censored at January 1999. Between November 2007 and December 2009 (the end of our sample period), new ORP participants are limited to investing through LOW or NEW. The last two columns of the table report the number of OUS employees who self-select into ORP versus PERS, the defined benefit retirement plan.

Table 2. Participant Summary Statistics, October 1996 - October 2007

ORP Participants who choose:	Any Provider (1)	HIGH (2)	Not HIGH (3)	LOW (4)
Sample Size	4,844	1,651	3,193	2,344
<i>% sample</i>	<i>100.0%</i>	<i>34.1%</i>	<i>65.9%</i>	<i>48.4%</i>
Monthly Salary (mean)	\$4,315	\$3,895	\$4,532	\$4,687
Monthly Salary (median)	\$3,750	\$3,450	\$3,894	\$4,000
Female	48.6%	50.2%	47.7%	45.7%
Age < 30	17.1%	20.0%	15.5%	13.2%
30 <= Age < 40	38.7%	36.2%	40.1%	41.9%
40 <= Age < 50	28.6%	28.0%	28.8%	29.2%
50 <= Age	15.6%	15.7%	15.6%	15.7%
Faculty Member	53.3%	50.9%	54.6%	55.8%
Business or Economics Department	3.5%	1.8%	4.4%	4.5%
Other Quantitative Department	18.9%	19.0%	18.9%	17.9%
Asian	7.5%	7.1%	7.7%	7.6%
Black	2.6%	2.8%	2.4%	2.6%
Hispanic	3.3%	3.3%	3.3%	3.7%
White	84.8%	84.4%	85.0%	84.6%
Other	1.8%	2.4%	1.5%	1.6%
PhD	48.9%	40.7%	53.1%	58.1%
Masters	29.4%	32.3%	27.9%	26.6%
Bachelors	21.7%	27.0%	19.0%	15.3%
	2,812	967	1,845	1,305
<i>% missing data</i>	<i>41.9%</i>	<i>41.4%</i>	<i>42.2%</i>	<i>44.3%</i>

Note: This table summarizes the characteristics of the sample of ORP participants during Regime 1 for whom we observe salary, gender, age, job status, and self-reported ethnicity. We report statistics for (1) the full sample, (2) the sample of participants that chooses HIGH, (3) the sample that chooses LOW, SMALL, or SMALLER, and (4) the sample that chooses LOW. Administrative data on the date of the choice between plans is left censored at January 1999. Job status and educational attainment are measured in the month that the participant begins working for OUS. Age and salary are measured in the month of the choice between plans or in January 1999. Faculty Member indicates whether participant i's job classification includes the string "Teach/Res". Business or Economics Department indicates whether participant i works in a business school or economics department. Other Quantitative Department indicates whether participant i's organizational description includes a reference to computer science, engineering, life science, mathematic, medicine, physical science, or a social science other than economics. We are missing data on educational attainment for more than 40% of our sample because these data

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

Dependent: Sample Period:	1 if new ORP participant chooses HIGH; 0 otherwise			
	10/96 - 10/07	2/99 - 10/07	2/99 - 10/07	2/99 - 12/04
	(1)	(2)	(3)	(4)
Salary	-0.0264 *** (0.0030)	-0.0274 *** (0.0044)	-0.0261 *** (0.0046)	-0.0172 ** (0.0073)
Female	-0.0150 (0.0135)	-0.0162 (0.0187)	-0.0167 (0.0181)	-0.0457 * (0.0268)
Age [30, 40)	-0.0470 ** (0.0221)	-0.0608 *** (0.0222)	-0.0741 *** (0.0226)	-0.0570 * (0.0340)
Age [40, 50)	-0.0149 (0.0345)	-0.0639 *** (0.0224)	-0.0859 *** (0.0221)	-0.0847 ** (0.0389)
Age [50, 100]	0.0027 (0.0596)	-0.0869 *** (0.0244)	-0.0958 *** (0.0263)	-0.1150 ** (0.0416)
Asian	0.0076 (0.0385)	0.0520 ** (0.0268)	0.0503 * (0.0280)	0.0732 * (0.0406)
Black	0.0357 (0.0493)	0.0572 (0.0581)	0.0750 (0.0626)	0.1124 (0.1002)
Hispanic	-0.0011 (0.0347)	0.0144 (0.0419)	0.0237 (0.0432)	0.0474 (0.0652)
Other Ethnicity	0.0849 * (0.0482)	0.0661 (0.0613)	0.0816 (0.0633)	0.0271 (0.1034)
Faculty	-0.0188 (0.0140)	-0.0310 ** (0.0158)	-0.0326 * (0.0198)	-0.0404 (0.0281)
Business & Economics	-0.1427 *** (0.0376)	-0.1050 ** (0.0471)	-0.0993 * (0.0491)	-0.1761 ** (0.0528)
Other Quantitative	0.0130 (0.0171)	-0.0018 (0.0203)	-0.0023 (0.0215)	-0.0355 (0.0294)
PhD				-0.1110 *** (0.0358)
Masters				-0.0339 (0.0295)
Return of S&P 500 index over prior 12 months		-0.0051 (0.0755)		
Lagged value of VIX		0.1450 (0.1874)		
Campus: Oregon State	-0.1287 *** (0.0175)	-0.1333 *** (0.0240)	-0.1453 *** (0.0253)	-0.2222 *** (0.0329)
Campus: Portland State	0.0099 (0.0205)	0.0270 (0.0259)	0.0161 (0.0255)	-0.0179 (0.0331)
Campus: Oregon Inst. of Technology	0.0935 (0.0939)	-0.0488 (0.0452)	-0.0510 (0.0463)	0.0397 (0.0536)
Campus: Eastern Oregon	-0.0293 (0.0498)	-0.0684 (0.0509)	-0.0700 (0.0511)	
Campus: Southern Oregon	-0.1151 *** (0.0330)	-0.1382 *** (0.0343)	-0.1527 *** (0.0329)	
Campus: Western Oregon	-0.0328 (0.0592)	-0.1070 ** (0.0459)	-0.1185 ** (0.0444)	
Office of the Chancellor	-0.1784 *** (0.0421)	-0.2115 *** (0.0423)	-0.2326 *** (0.0354)	

Date of choice fixed effects?	No	No	Yes	Yes
N	4,844	3,366	3,366	1,583
Pseudo-R2	0.0368	0.0464	0.0842	0.1200

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 new ORP participants 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 columns (2), (3), and (4) begins in February 1999. Because data on participant *i*'s educational attainment were only collected through December 2004 and only by four of the campuses, the sample period in column (4) ends in December 2004, and the sample is limited to participants employed by Oregon Institute of Technology, Oregon State, Portland State, or University of Oregon for whom we observe data on educational attainment. Demographic controls include salary, gender, age, self-declared ethnicity (the omitted category is "White"), and educational attainment (the omitted category is "Bachelors"). We also control for whether the participant is faculty or staff, and for whether we classify the department as business and economics, quantitative but not business or economics, and all of the rest. To control for economic conditions in the month of the choice, column (2) controls for the return on the S&P 500 index over the prior 12 months and for the value of the VIX index at the beginning of the month of the choice. Alternatively, columns (3) and (4) 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 versus LOW from a survey of current ORP participants

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

	Do you have an ongoing relationship with a financial adviser?		"I would feel comfortable making changes to my equity and bond balance without consulting my adviser"		How did you primarily decide on the fraction to invest in stocks?			
	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
LOW	452	32.7%	144	43.8%	369	44.7%	45.3%	10.0%
HIGH	259	58.7%	146	24.7%	214	21.5%	74.3%	4.2%
Difference		26.0%		-19.1%		-23.2%	29.0%	-5.8%
P-value		0.000		0.001		0.000	0.000	0.012

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

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

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

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

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

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

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

	Financial Literacy		Choice between jobs with certain versus uncertain income					
	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%
LOW	401	93.3%	285	20.0%	268	47.8%	311	83.9%
HIGH	240	90.0%	164	17.7%	162	45.1%	176	77.3%
Difference		-3.3%		-2.3%		-2.7%		-6.6%
P-value		0.034		0.547		0.587		0.072

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

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

Sample period:		Regime 1		Regime 2	
Provider	Default	N	Invest 100% in Default?	N	Invest 100% in Default?
<i>Panel A. Sample of new participants for which we observe portfolio holdings in month 6</i>					
HIGH	Fixed annuity	1,493	2.9%		
LOW	Money market fund	2,347	9.5%	256	21.5%
NEW	Target-date fund			272	64.0%
		<u>3,840</u>	<u>7.0%</u>	<u>528</u>	<u>43.4%</u>
<i>Panel B. Subsample of new participants for which we can estimate Pr(HIGH) in Table 3 Column (1)</i>					
HIGH	Fixed annuity	1,348	2.9%		
LOW	Money market fund	2,020	10.0%	240	21.7%
NEW	Target-date fund			256	65.2%
		<u>3,368</u>	<u>7.2%</u>	<u>496</u>	<u>44.2%</u>
<i>Panel C. Subsample of new participants for which we can estimate Pr(HIGH) in Table 3 Column (3)</i>					
HIGH	Fixed annuity	862	2.0%		
LOW	Money market fund	1,465	12.6%	240	21.7%
NEW	Target-date fund			256	65.2%
		<u>2,327</u>	<u>8.7%</u>	<u>496</u>	<u>44.2%</u>

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

Table 6. Using Predicted Demand for HIGH to Predict Demand for Default Investment Option Before and After HIGH is Dropped

Dependent: Sample Period: ORP Providers:	1 if new participant contributes 100% to default investment option in month 6					
	Regime 1		Regime 2			
	HIGH or LOW		LOW or NEW		NEW only	
	(1)	(2)	(3)	(4)	(5)	(6)
Pr(HIGH)	-0.0135 (0.0517)		0.5206 *** (0.1417)		0.7470 *** (0.2179)	
Pr(HIGH) in top quarter		0.0178 (0.0154)		0.1279 (0.0782)		0.1748 ** (0.0831)
Pr(HIGH) in bottom quarter		0.0117 (0.0127)		-0.0494 (0.0484)		-0.0781 (0.0575)
Constant	0.0911 *** (0.0165)	0.0792 *** (0.0062)	0.2782 *** (0.0445)	0.4230 *** (0.0269)	0.4165 *** (0.0688)	0.6277 *** (0.0311)
P-value coef are equal		0.6820		0.0157 **		0.0038 ***
Date of Choice FE?	Yes	Yes	Yes	Yes	Yes	Yes
N	2,327	2,327	496	496	256	256
R2	0.0705	0.0712	0.0747	0.0766	0.1434	0.1452

Note: In this table, we predict whether new ORP participant i is contributing 100% of her retirement contributions to the provider j 's default investment option five months after her first contribution to provider j . Estimation is via OLS. We estimate separate specifications for participants who have access to HIGH (i.e., participants whose first contribution is before 10/07) and participants who do not have access to HIGH (i.e., participants whose first contribution is after 10/07). The independent variable of interest is the predicted probability that participant i chooses HIGH based on the estimated coefficients in Column (2) of Table 3. Because Column (2) of Table 3 is restricted to participants for whom we observe the date of the choice, we are able to include a separate fixed effect for the year-month of the choice. The last two columns are restricted to the subset of new participants who choose to invest through NEW, which offers target-date funds as its default investment option. Standard errors are clustered on the date of the choice. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 7. Comparing Actual Portfolios to Counterfactual Portfolios Based on Target-Date Funds, 1999-2009

Panel A. HIGH									
	Actual				Target-Date Fund Benchmark				
	Volatility of		CAPM Beta	Broker Fee	Volatility of		CAPM Beta	Broker Fee	
	Annual Return	Monthly Return			Annual Return	Monthly Return			
1999	29.21%	3.93%	0.796	0.93%	24.53%	3.14%	0.695	0.00%	
2000	-13.53%	5.97%	0.854	0.93%	-2.88%	4.07%	0.758	0.00%	
2001	-18.72%	6.99%	1.117	0.93%	-9.34%	4.46%	0.724	0.00%	
2002	-18.12%	4.56%	1.033	0.92%	-14.19%	3.98%	0.690	0.00%	
2003	23.34%	2.69%	0.753	0.92%	25.53%	2.37%	0.673	0.00%	
2004	8.93%	2.18%	0.808	0.91%	9.80%	2.01%	0.838	0.00%	
2005	4.52%	2.06%	0.857	0.91%	8.09%	2.04%	0.789	0.00%	
2006	10.08%	1.61%	0.787	0.91%	12.22%	1.87%	0.942	0.00%	
2007	4.78%	2.31%	0.812	0.85%	8.87%	2.40%	0.834	0.00%	
2008	-32.04%	5.72%	0.793	0.84%	-34.83%	5.94%	0.903	0.00%	
2009	25.65%	5.14%	0.815	0.85%	29.77%	5.30%	0.819	0.00%	
1999-2009	1.84%	3.82%	0.853	0.90%	4.82%	3.39%	0.797	0.00%	

Panel B. LOW									
	Actual				Target-Date Fund Benchmark				
	Volatility of		CAPM Beta	Broker Fee	Volatility of		CAPM Beta	Broker Fee	
	Annual Return	Monthly Return			Annual Return	Monthly Return			
1999	19.84%	2.87%	0.705	0.00%	25.18%	3.21%	0.709	0.00%	
2000	-7.83%	4.19%	0.683	0.00%	-3.16%	4.14%	0.772	0.00%	
2001	-10.76%	4.71%	0.732	0.00%	-9.46%	4.50%	0.730	0.00%	
2002	-14.39%	3.72%	0.735	0.00%	-14.48%	4.04%	0.701	0.00%	
2003	19.96%	1.97%	0.585	0.00%	25.86%	2.40%	0.684	0.00%	
2004	8.66%	1.52%	0.567	0.00%	9.82%	2.01%	0.842	0.00%	
2005	6.20%	1.50%	0.611	0.00%	8.13%	2.05%	0.792	0.00%	
2006	10.73%	1.26%	0.560	0.00%	12.18%	1.87%	0.939	0.00%	
2007	8.01%	1.60%	0.620	0.00%	8.86%	2.39%	0.830	0.00%	
2008	-22.19%	3.72%	0.541	0.00%	-34.85%	5.94%	0.903	0.00%	
2009	15.25%	3.20%	0.534	0.00%	29.77%	5.31%	0.820	0.00%	
1999-2009	3.12%	2.56%	0.601	0.00%	4.87%	3.50%	0.817	0.00%	

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

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

Dependent:	Annual Portfolio Return		Volatility of Monthly Returns		CAPM Beta		6-Factor Alpha		Sharpe Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Comparing Actual Portfolios to Counterfactual Portfolios										
HIGH	-0.0321 *** (0.0109)		0.0037 (0.0027)		0.0533 (0.0548)		-0.0211 ** (0.0103)		-0.1436 ** (0.0571)	
LOW		-0.0174 (0.0288)		-0.0093 *** (0.0029)		-0.2148 *** (0.0418)		-0.0091 (0.0068)		-0.1194 (0.0881)
Year fixed effects?	No	No	No	No	No	No	No	No	No	No
N	5,912	15,616	5,912	15,616	5,056	15,579	4,253	15,481	5,912	15,616
R2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B. Comparing Actual Portfolios of HIGH and LOW										
HIGH?	-0.0143 (0.0211)	-0.0198 (0.0145)	0.0115 *** (0.0023)	0.0008 (0.0035)	0.2303 *** (0.0269)	-0.0374 (0.0683)	-0.0115 (0.0125)	-0.0114 (0.0110)	-0.3304 (0.2079)	0.0486 (0.3686)
Pr(HIGH) * HIGH?		0.0122 (0.0333)		0.0162 ** (0.0073)		0.4363 *** (0.1476)		-0.0014 (0.0091)		-0.7742 (0.5019)
Pr(HIGH) * LOW?		-0.0032 (0.0332)		-0.0147 *** (0.0034)		-0.3368 *** (0.0608)		-0.0015 (0.0061)		0.2971 (0.2766)
Ho: Interactions equal		0.7805		0.0001 ***		0.0000 ***		0.9879		0.0738 *
Year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,528	21,528	21,528	21,528	20,635	20,635	19,816	19,816	21,528	21,528
R2	0.7748	0.7748	0.4590	0.4639	0.1324	0.1424	0.1386	0.1386	0.0436	0.0437

Note: The unit of observation is the portfolio of ORP participant i in calendar year t . The sample period is 1999-2009. Portfolio characteristics include the portfolio's annual after-fee return, volatility of monthly returns, lagged CAPM beta, six-factor alpha, and Sharpe ratio. Characteristics of actual portfolios are estimated from beginning of the year holdings, assuming no additional contributions into ORP during year t . Characteristics of counterfactual portfolios are based on the Fidelity TDF to which participant i is assigned. The OLS regressions in Panel A separately test for differences between the actual and counterfactual portfolios of HIGH and LOW investors. The dependent variable in each regression is the difference between the characteristics of participant i 's actual and counterfactual portfolios. The numerator of the Sharpe ratio is the difference in monthly returns and the denominator is the standard deviation of the difference in monthly returns. The OLS regressions in Panel B compare the portfolios of HIGH and LOW investors. The dependent variable is the characteristics of participant i 's actual portfolio. The independent variables include a dummy variable indicating whether participant i invests through HIGH, the predicted probability that participant i invests through HIGH interacted with the dummy variable indicating whether participant i invests through HIGH, the predicted probability that participant i invests through HIGH interacted with the dummy variable indicating whether participant i invests through LOW, and a full set of calendar year fixed effects. The predicted probabilities are based on the specification in column (1) of Table 3, which controls for salary, gender, age, and campus. We report the p-value from the test that the coefficients on the two interaction terms are equal. To allow for correlations both in annual portfolio returns across participants in year t and in participant i 's annual portfolio returns across years, we cluster standard errors on calendar year t and participant i . Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table 9. Modeling Allocation of Retirement Contributions Across Funds

Dependent: Sample Period: Sample of Investments:	Fraction of Retirement Contributions Allocated to Fund j					
	<i>Month 1 (1st ORP Contribution)</i>			<i>Month 24</i>		
	<i>All</i>	<i>Debt & Equity</i>	<i>Equity</i>	<i>All</i>	<i>Debt & Equity</i>	<i>Equity</i>
	<i>(1)</i>	<i>(2)</i>	<i>(3)</i>	<i>(4)</i>	<i>(5)</i>	<i>(6)</i>
Lagged Return * LOW	0.224 ** (0.093)	0.133 * (0.077)	0.218 * (0.120)	0.300 *** (0.102)	0.143 (0.103)	0.107 (0.161)
Not Broker Fee * LOW	0.182 (0.181)	-0.139 (0.179)	-1.194 *** (0.461)	-0.468 *** (0.099)	-0.880 *** (0.123)	-0.662 *** (0.159)
Lagged Return * HIGH	0.448 *** (0.045)	0.443 *** (0.043)	0.448 *** (0.049)	-0.073 (0.051)	-0.038 (0.047)	-0.012 (0.056)
Not Broker Fee * HIGH	-0.280 *** (0.011)	-0.253 *** (0.010)	-0.271 *** (0.013)	-0.245 *** (0.012)	-0.262 *** (0.013)	-0.312 *** (0.028)
Broker Fee	0.455 *** (0.029)	0.406 *** (0.030)	0.386 *** (0.027)	0.436 *** (0.055)	0.442 *** (0.055)	0.376 *** (0.056)
Ho: Lagged Return: LOW = HIGH	0.004	0.000	0.051	0.001	0.108	0.485
Ho: Lagged Return: LOW = HIGH = 0	0.000	0.000	0.000	0.004	0.270	0.783
Ho: Not Broker Fee: LOW = HIGH	0.011	0.524	0.045	0.024	0.000	0.030
Ho: Not Broker Fee: LOW = HIGH = 0	0.000	0.000	0.000	0.000	0.000	0.000
Participant controls?	Yes	Yes	Yes	Yes	Yes	Yes
Fund-level controls?	Yes	Yes	Yes	Yes	Yes	Yes
Date-by-Provider FEs?	Yes	Yes	Yes	Yes	Yes	Yes
N	72,163	66,881	39,208	66,839	62,011	36,127
Adj. R2	0.2038	0.2217	0.2859	0.1853	0.1782	0.2369

Note: In this table, we test whether the fraction of retirement contributions allocated to fund j responds to the level of fund j's return over the prior 12 months, the level of fund j's fees that are paid to a broker, and the level of fund j's fees that are not paid to a broker. The sample includes one observation for each investment option available to a HIGH or LOW participant in month t. We estimate one set of Tobit regressions in the first month that participant i contributes to HIGH or LOW and another set of Tobit regressions in month 24. The independent variables of interest are the lagged after-fee return of fund j interacted with dummy variables indicating whether fund j is available through HIGH or LOW, the broker fee associated with fund j (which is zero from LOW), and the fund's annual fee minus the broker fee. (No fund is simultaneously available through both providers.) In addition, all regressions include the full set of participant controls and campus fixed effects from column (2) of Table 3, lagged factor loadings from the six-factor model, and date-by-provider fixed effects. We exclude participants who allocate 100% of their retirement contribution to the default investment option. Standard errors are clustered on the month of the choice. We report the p-values of the hypotheses tests that the estimated coefficients on the lagged return variables are equal, and that they are both equal to zero. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.

Table A1. Overview of HIGH and LOW Investment Menus

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

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

Table A2. Overview of Investment Menus in 2002

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

Note: This table summarizes the investment menu options that OUS presented to new employees in 2002 in the documents comparing PERS and ORP.

Table A3. Demand for ORP versus PERS

Dependent: Providers: Sample Period:	1 if OUS employee chooses PERS			
	PERS or ORP 10/96 - 10/07	PERS or ORP 2/99 - 10/07	PERS or ORP 2 FE	PERS or ORP 2/99 - 12/04
	(1)	(2)	(2 FE)	(3 FE)
Salary				
Female	0.0177 (0.0145)	0.0021 (0.0070)	0.0024 (0.0069)	-0.0048 (0.0114)
Age [30, 40)	-0.1694 *** (0.0356)	-0.1246 *** (0.0150)	-0.1123 *** (0.0115)	-0.0540 *** (0.0166)
Age [40, 50)	-0.1592 *** (0.0609)	-0.0803 *** (0.0145)	-0.0757 *** (0.0125)	-0.0046 (0.0183)
Age [50, 100]	-0.0444 (0.0585)	0.0277 ** (0.0110)	0.0152 (0.0124)	0.0817 *** (0.0178)
Asian	0.0057 (0.0190)	-0.0124 (0.0118)	-0.0118 (0.0108)	0.0123 (0.0166)
Black	-0.0528 ** (0.0231)	-0.0658 *** (0.0227)	-0.0691 *** (0.0256)	-0.1077 *** (0.0461)
Hispanic	0.0379 *** (0.0126)	0.0342 ** (0.0139)	0.0365 *** (0.0127)	0.0260 (0.0225)
Other	0.0265 (0.0188)	0.0178 (0.0195)	0.0217 (0.0186)	0.0042 (0.0321)
Faculty	-0.0484 ** (0.0256)	-0.0309 (0.0249)	-0.0316 * (0.0191)	0.0330 (0.0223)
Business & Economics	-0.0985 *** (0.0284)	-0.0727 *** (0.0301)	-0.0599 ** (0.0276)	-0.0495 (0.0374)
Other Quantitative	-0.0724 *** (0.0082)	-0.0667 *** (0.0098)	-0.0468 *** (0.0093)	-0.0174 (0.0146)
PhD				-0.2082 *** (0.0227)
Masters				-0.0384 ** (0.0165)
Return of S&P 500 index over prior 12 months		0.0947 (0.1366)		
Lagged value of VIX		0.5966 ** (0.2422)		
Campus: Oregon State	0.0151 (0.0124)	0.0157 (0.0147)	0.0248 * (0.0126)	0.0596 *** (0.0140)
Campus: Portland State	0.1428 *** (0.0188)	0.1236 *** (0.0118)	0.1166 *** (0.0095)	0.1284 *** (0.0153)
Campus: Oregon Inst. of Technology	-0.0208 (0.0317)	0.0060 (0.0256)	0.0240 (0.0189)	0.0604 ** (0.0237)
Campus: Eastern Oregon	0.0804 *** (0.0179)	0.0635 *** (0.0170)	0.0807 *** (0.0136)	
Campus: Southern Oregon	0.1620 *** (0.0262)	0.1295 *** (0.0145)	0.1336 *** (0.0094)	
Campus: Western Oregon	0.0731 *** (0.0144)	0.0669 *** (0.0166)	0.0816 *** (0.0128)	
Office of the Chancellor	-0.0587 * (0.0144)	-0.0803 * (0.0166)	-0.0483 (0.0128)	

	(0.0366)	(0.0473)	(0.0457)	
N	20,563	16,459	16,459	6,927
Pseudo-R2	0.0720	0.0691	0.1772	0.2272

Note: Probits mirror those in Table 3. Dependent variable equals one if OUS employee *i* chooses PERS as his retirement plan and zero if he chooses ORP. Independent variables are the same as in Table 3, except that we cannot include monthly salary because we only observe monthly salary for the subset of employees who choose ORP. The table reports marginal effects estimated via probit. Standard errors are clustered on the date of the choice. Statistical significance at the 10-percent, 5-percent, and 1-percent level (in two-sided tests) is denoted by *, **, and ***.