Barking Up The Wrong Tree: Return Chasing in Mutual Funds

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Abstract

This paper examines how investors allocate their savings with a limited choice set. Using a hand-collected data set on firm-level investment decisions in 401(k) plans, we show that investors blindly follow unadjusted returns rather the CAPM alpha or Morningstar rating when investing in mutual funds. Our result informs recent debates on the drivers of fund flow. To explain the differences in results between ours and prior literature, we propose an explanation through the wealth inequality channel. We show that 14% of the population with high wages and financial market participation rates hold 51% of the wealth and direct their savings based on the CAPM alpha, whereas the remaining 86% of the population chase unadjusted returns. Our results serve as a wake-up call to the lack of financial literacy in 401(k) markets.

Keywords: Mutual funds, defined contribution, fund flows, wealth inequality, financial literacy

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1 Introduction

How investors allocate their savings to mutual funds is one of the most important questions in the asset management literature. Recent studies suggest that investors value funds that deliver superior returns excess of the market exposure (Barber, Huang, and Odean (2016), Berk and Van Binsbergen (2016)). These studies implicitly assume that investors are free to invest in any funds in the market without any searching or participation cost. However, researchers have shown in various economic and psychological settings that, investors have limited attention and face selection problems (Barber and Odean (2007), Lacetera, Pope, and Sydnor (2012)). In this paper, we study the asset selection problems in employer-sponsored defined contribution (DC) plans, where employees' investment options are naturally bounded. Our results suggest that, at the firm level, investors care only about unadjusted returns, but pay little attention to systematic risks or third-party ratings (Ben-David, Li, Rossi, and Song (2019)). The seemingly inconsistent results between ours and Barber et al. (2016) can be explained by the wealth inequality channel. In particular, over 51% of the aggregated wealth is held by only 14% of the population, who are more sophisticated in financial markets and invest their money following the CAPM alpha ranking, whereas the remaining 86% of the population blindly follow unadjusted returns. Therefore, in aggregate, flows respond to the CAPM alpha. Our paper is the first to examine the flow-performance relation using micro-level data. We also reconcile the differences in flow-performance results among prior literature by providing an economic explanation through the wealth inequality channel. Moreover, we highlight the lack of financial sophistication among investors in DC markets, which has important implications and contributes to the financial literacy literature.

To study how investors evaluate fund performance and make investment decisions, we hand-collect a large sample of DC plans for over 1,500 US public firms between 1993 and 2016 from annual filings Form 11-K. The data contain information on the funds offered to employees and their asset allocation decisions with an annual frequency. The granularity of the data provides an ideal setting for us to study investors' investment decisions under the bounded choice set. We can identify the rankings of mutual funds faced by investors and study the flow-performance relation within the limited options. Moreover, DC plans have grown popular and become a large part of the market.[1] The employee is responsible for choosing which funds to invest in from the plan. Such a plan has numerous advantages, such as tax savings and contribution matching by employers. Despite the importance and benefits of the DC plans, little is known about how investors allocate their savings. The lack of evidence on the pattern and quality of investment decisions is disconcerting, given that employees rely heavily on their 401(k) to generate retirement income.

We begin our analysis by estimating a linear regression in which the dependent variable is the fund flow, and key independent variables are various fund performance measures. The regression is similar to the horse race panel regression in Barber et al. (2016), but is estimated at the micro level. The model allows us to take into account the number of investment options employees face when they allocate their savings. We show that investors' asset allocation decisions within the plan only depend on the unadjusted return. The result is in direct contrast to Barber et al. (2016), in which they suggest investors are able to calculate the CAPM alpha and invest accordingly.

To carefully establish the flow-return relation, we run two additional tests that are less parametric than the linear regression model. First, we exploit the within-plan variations in performance rankings resulted from different performance metrics used by investors. For example, a fund can be ranked in the top tier using unadjusted returns, but in the middle tier using the CAPM alpha. The test is first developed in Barber et al. (2016), and we extend their analysis and explore flow-performance relation within the plan. We then run pairwise comparisons among alternative performance metrics. Flows are more responsive to funds with higher ranks of unadjusted returns than the CAPM alpha, four-factor alpha, or Morningstar ratings.

Our second non-parametric test shows the unadjusted return is "the" ranking criteria for

[1] Over 55 million American workers are active participants, with over $4.7 trillion invested by the end of 2016. See Investment Company Institute (https://www.ici.org/policy/retirement/plan/401k/faqs_401k).

investment by studying the explanatory power of alternative performance metrics on fund flows, following Ben-David et al. (2019). In this paper, they show that the linear regression model with time fixed-effects overweights cross-sections with extreme market returns, which bias the finding towards CAPM alpha being the correct metrics. Within the plan, we rank funds by each performance measure into quintiles. For each performance metric, we examine the difference in flows between the top and bottom quintile funds. Our results show that the unadjusted return ranking is the best predictor for both flows in dollars and percentage points.

Investors blindly following unadjusted returns seems striking to economists, who are trained to take into account any systematic exposures when they evaluate performance. However, it does not necessarily imply that investors in our sample trade irrationally. It could simply be that following raw returns maximizes their expected utility under their belief. To test this hypothesis, we assume employees in each plan as a representative agent with a mean-variance utility function, which depends on his/her choice of performance measure. Given the assets in place from the prior year, the agent chooses the best asset allocation in each year to maximize the utility. We then compare the distance between the realized asset allocation and the "optimal" mean-variance portfolio. We show that the realized asset allocation is the closest to the efficient portfolio using unadjusted returns, rather than risk-adjusted alphas. Therefore, the observed asset allocation decisions are consistent with investors' belief of unadjusted returns serving as the ranking criteria.

Our results emphasize the flow-return relation at the micro level, whereas the prior literature focuses on the aggregate level. To explain the differences in results between ours and Barber et al. (2016), we aggregate our data into fund level and re-run the horse race among alternative performance metrics. At the aggregate level, only the CAPM alpha predicts future flows, which is different from our findings but consistent with the literature. Therefore, our micro-level results are not driven by sample selections.

To explain these different results between the micro level and aggregate level, we offer a potential explanation through the wealth inequality channel. In particular, a small proportion of employees possess a substantial portion of savings, and their investment decision follows the CAPM alpha, while the remaining employees chase raw returns. Therefore, flow relation is dominated by the majority of the population, which favors unadjusted returns at the micro level, but tilts towards the CAPM alpha in the aggregate. In other words, wealth is unequally distributed, and high-savings employees favor the CAPM alpha over unadjusted returns.

To test the wealth inequality hypothesis, we split our sample by the average savings per employee into four groups. We find that only the highest savings employees allocate their savings towards funds based on the CAPM alpha. This group represents the wealthiest employees in our sample, with only 14% of the population holding more than 51% of the savings. The highest savings group saves on average \$0.18 million per employee, which is over 14 times greater than the lowest savings group and over two times greater than the second-highest savings group.

The massive difference in savings in the 401(k) cannot be attributed to either firms' contribution matching policy or working tenures. First, firms can only match up to 100% of an employee's contribution, so that the variation in firm's matching policy cannot explain the gap in employees' 401(k) savings. Second, the saving gap is not driven by long working tenures of the highest savings group. The average difference in firm's ages between high and low saving groups is ten years, and the difference in savings is \$0.17 million. If the age difference explains the saving gap, employees have to earn an annual wage of \$147,920, which is much higher than the average income per capita of \$48,150 in the U.S. We also infer employee average age using the names of the Target Date Funds, which typically contains the year of retirement. The difference in average ages between the highest savings and lowest savings groups is 2.3 years, which clearly cannot drive the savings gap.

We argue that the difference in the saving gap is driven by the difference in the participation rate and wages, which in turn reflects the different level of financial sophistication. A high participation rate implies that employees are comfortable investing and have some level of financial sophistication. A high wage implies that employees are probably more skilled or have higher education degrees, which also suggests financial sophistication. As a result, the highest savings group with a high level of financial sophistication selects funds based on the CAPM alpha.

Lastly, we show that employees walk away from substantial capital gains by chasing unadjusted returns. For each plan at each year, we bootstrap hypothetical flows, assuming that investors direct flows based on the CAPM alpha rather than unadjusted returns. The realized asset allocation performs worse than the hypothetical allocation, indicating that investors can benefit by taking into account the market exposure when evaluating fund performance. However, both strategies significantly underperform the S&P 500 index fund, which is available to most 401(k) plans. Our result suggests that unsophisticated investors are better off to avoid active funds and invest in index funds.

In summary, we find strong evidence that employees allocate their savings following the unadjusted returns, which informs the recent debates (Barber et al. (2016), Berk and Van Binsbergen (2016), Ben-David et al. (2019), Evans and Sun (2018)). The literature mainly studies the flow-performance relation at the aggregate level, whereas our paper is the first to provides evidence at the micro level. One advantage of our study is that we can identify the performance rankings faced by investors given their limited choices, which is impossible to achieve with the aggregated data. Unlike Ben-David et al. (2019) and Evans and Sun (2018), we explore the cross-section variation in investing patterns to explain the difference in results between our paper and Barber et al. (2016). We show that a small population in our sample holds a large proportion of wealth and favors the CAPM alpha over other performance measures, which drives the flow-performance relation towards the CAPM territory in the aggregate level.

Our paper also contributes to the wealth inequality literature and the rapidly growing financial literacy literature. The saving gap we identified can be explained by the difference in

401(k) participation rate and the difference in wages. Lusardi, Michaud, and Mitchell (2017) shows that financial knowledge is a crucial determinant of wealth inequality. Campanale (2007) shows that the difference in portfolio returns between the wealthy and poor agents can explain wealth inequality.

The rest of this study is organized as follows. Section 2 describes the dataset. Section 3 shows the flow-return relation at the micro level. Section 4 discusses the difference in flow-performance relations between the micro level and the aggregate level. Section 5 concludes.

2 Data

2.1 Data sources

Employee's investment options are hand-collected from annual Form 11-K filings with the U.S. Securities and Exchange Commission for 1,551 U.S. public firms from 1993 to 2016. Firms are required to disclose Form 11-K if they offer their company stock to employees in the 401(k) plans. In this form, firms report the menu of investment options, such as mutual funds, firm's own stock, other firms' stocks, etc., available to their employees and the current investment value of each option. For a few firms that have multiple 401(k) plans for different subsidiaries within a year, we aggregate them to one plan.

Fund data is from the Center for Research in Security Prices (CRSP) survivorship-bias-free mutual fund database. Fund expense ratios and returns at share class level are aggregated to one observation per fund using their previous month total net assets (TNA) as weights. Fund TNA are the sum of TNA of all share classes within the same fund. Since most funds are listed on 11-K without share class information, we use fund-level data for funds in these plans. In addition, information on the number of employees is from Compustat.

2.2 Sample statistics

The final sample has 13,914 firm-year observations and 153,442 firm-fund-year ones. The proportions of firms across Fama-French 12 industries[2] are very closed to those of all public firms. Within each industry, the fraction of firms in the sample is 12% on average. This number varies from 9% to 15% for all industries except that the sample covers more firms in utility industry (32%) but fewer firms in healthcare (5%) and business equipment (6%) ones. In term of market value, 80% of our firms are larger than the median firms that operate in the same industry, and 40% are in the top size quintile firms.

Table 1 provides descriptive statistics by year at the firm-level. The average and median plan size are \$820 and \$165 million, and they increase over the years except for recession periods in 2001 and 2007-2009, which causes depreciation in plan value. In our sample, the total investment in 401(k) account has grown from \$45 billion in 1993 to around \$800 billion in 2016. The increasing number of firms that offer 401(k) contributes to this trend. In addition, these amounts represent on average of 21% of plan assets of all public and private firms[3] whose plans have 100 or more participants.

Employees invest substantial capital in their firm's stock, 82% of plan asset in 1993. However, this figure declined to 71% in 2016. Employees not only bet less on their firms but also have more investment options over the years. This diversification benefit is attributed to the growth in the mutual fund industry. With lots of different funds offered, employees have more choices in their plans, i.e., 17 funds in 2015 compared to 3 in 1993. This figure is smaller in 2016 since we have fewer firms in this year as firms could potentially file in a late fiscal year-end. We then split funds into three categories: equity funds, bond funds, and a blend of these two. When facing these, employees allocate 67% of their capital to equity

[2]Fama-French 12 industries consist of business equipment, chemical, consumer durable, consumer non-durable, energy, finance, healthcare, manufacturing, telecommunication, utility, wholesale and retail, and others.

[3]Data on 401(k) assets for all firms are in Private Pension Plan Bulletin - Abstract of Form 5500 Annual Reports from the Department of Labor: https://www.dol.gov/agencies/ebsa/researchers/statistics/retirement-bulletins/private-pension-plan.

funds and 20% to bond funds. These allocations are pretty stable over the years.

[Insert Table 1 near here]

3 Micro-level Flow Analysis

Even though both employees and employers contribute to 401(k) retirement plans, employees are responsible for the asset allocation. With the list of mutual funds provided from employers, they allocate their capital across these options to generate retirement income. Therefore, our dataset provides a perfect laboratory to study how investors evaluate fund performance and make investment decisions. This section is devoted to it.

We use a variety of methods to examine what performance measures investors use to direct their flow of capital, which is defined as follows:

$$Flow_{pft} = \frac{V_{pft} - V_{pf,t-1}(1 + R_{ft})}{\sum_{f \in \Theta_{p,t-1}} V_{pf,t-1}}, \tag{1}$$

where V_{pft} is the investment value in fund f from participant of firm p's 401(k) plan in year t and R_{ft} is the fund's net of fee return during year t. $\Theta_{p,t-1}$ is the set of funds in firm p's plan in year $t-1$, hence the denominator represents the firm's plan size in that year, excluding stock holding.[4]

3.1 Panel regression

We first study the flow-performance sensitivity by estimating the following regression:

$$Flow_{pft} = \beta_0 PERF_{f,t-1} + \mathbf{X'}_{pft}\boldsymbol{\beta}_1 + \mu_t + \gamma_p + \epsilon_{pft}, \tag{2}$$

[4] Our results are robust if we also include stock holding in the denominator.

where $PERF_{f,t-1}$ is fund f's performance measures in year $t-1$. There are four performance measures used in this paper: [1] fund's net of fee return (R_{ft}), [2] CAPM alpha (α_{ft}^{CAPM}), [3] 4-factor alpha ($\alpha_{ft}^{4Factor}$), and [4] Morningstar risk-adjusted return ($MStar\ return_{ft}$). $\mathbf{X}_{pft}$ represents plan and fund characteristics, which are logarithm of the number of funds, firm return, and firm stock flow to 401(k) plan, fund expense ratio, fund turn over, logarithm of total fund net assets and standard deviation of fund return. μ_t and γ_p are time and firm fixed effects.

For CAPM and 4-factor alphas, they are estimated monthly based on a rolling estimation window following Barber et al. (2016). For each fund f in month m, we estimate the following time-series regression using thirty six months of returns:

$$R_{f\tau} - RF_{\tau} = a_{fm} + \mathbf{F}'_{\tau}\boldsymbol{\beta}_{fm} + \varepsilon_{f\tau}, \quad \tau = m-1, ..., m-36 \tag{3}$$

where RF_{τ} is risk-free rate in month τ and $\mathbf{F}_{\tau}$ is the vector of factor returns. For equity and balanced funds, we use CRSP value-weighted stock index (market) factor in the CAPM model and use Carhart (1997) 4-factor model which includes market, size, value, and momentum factors. For bond funds, we use the U.S. aggregate bond index in the CAPM model, and use the following four factors in the 4-factor model: market, the U.S. aggregate bond index, the U.S. high-yield bond index, and the mortgage-backed security index. These factors have been used in Ma, Tang, and Gomez (2019), Cici and Gibson (2012), and Elton, Gruber, and Blake (1995). We then estimate alpha for fund f in month m as follows:

$$\hat{a}_{fm} = R_{fm} - RF_m - \mathbf{F}'_{\mathbf{m}}\hat{\boldsymbol{\beta}}_{fm} \tag{4}$$

where $\hat{\boldsymbol{\beta}}_{fm}$ is estimated from equation 3. Since our data is at annual frequency, an annual alpha of fund f is calculated using the 12 monthly alpha in year t:

$$\alpha_{ft} = \prod_{j=0}^{11}\left(1 - \hat{a}_{f,t-\frac{j}{12}}\right) - 1. \tag{5}$$

Fund's net of fee return (R_{ft}) is annualized in the same way.

To assign star rating, Morningstar uses risk-adjusted return $MRAR$ to rank fund[5] f at time t as follows:

$$MRAR_{ft}(\gamma, T) = \left[\frac{1}{T}\sum_{j=0}^{T-1}(1 + ER_{f,t-j})^{-\gamma}\right]^{-\frac{12}{\gamma}} - 1, \tag{6}$$

where γ is the risk aversion coefficient and $ER_{f,t-j} = \dfrac{R_{f,t-j} - RF_{t-j}}{1 + RF_{t-j}}$ is the geometric return in excess of the risk-free rate. Morningstar uses $\gamma = 2$ to rank funds. We use the most recent 36 months of return to compute Morningstar return for the fund at year t, ie. $\textit{MStar return}_{ft} = MRAR_{ft}(2, 36)$. This value is expressed as an annualized return.

When we examine the predictive power of these four performance measures to future flows separately, it shows in columns (1) to (4) in Table 2 that each of them significantly determines flows. The flow-performance sensitivity is similar across performance measures with the value of 0.02 except for 4-factor alpha that has not only a smaller effect but also a weaker statistical significance level.

To compare predictive powers across models, we first make pairwise comparisons between the fund's net return and other measures. Column (5) reports the regression results of future flows on net return and CAPM alpha. It shows that the coefficient on CAPM alpha becomes not only much smaller but also insignificant, while that on net return is 0.017 and statistically significant at 5% level. The results are similar when comparing net return with 4-factor alpha or Morningstar return in columns (6) and (7). In addition, coefficients on net return stay almost the same across pairwise comparisons with the average value of 0.02. Our finding suggests that when fund net return increases by 1%, there is additional 0.02% of flow, which is equivalent to $40,000 extra for funds in the average firm's plan.

Lastly, we run the horse race among these four performance measures. Results in column (8) show that net return is the winner while the others do not drive future flows. In column

[5] The Morningstar Rating for Funds is available at `https://s21.q4cdn.com/198919461/files/doc_downloads/othe_disclosure_materials/MorningstarRatingforFunds.pdf`.

(9), we add the investment category fixed effects, and our results are robust.

[Insert Table 2 near here]

3.2 Pairwise model horse race

In the previous section, we examine the flow-fund performance sensitivity assuming that they have the linear relation. However, the relation could be non-linear. To address this issue, following Barber et al. (2016), we compare net return model with the others by estimating the relation between flows and a fund's quintile ranking based on their performance metrics within the firm. Specifically, we run the following regression:

$$Flow_{pft} = \sum_i \sum_j b_{ij} D_{ijpft} + \mathbf{X}'_{pft}\mathbf{c} + \mu_t + \gamma_p + \zeta_{pft}, \tag{7}$$

where D_{ijpft} is a dummy variable that equals one if fund f of firm p in year t is in quantile i based on the fund net return and quantile j based on other performance measures, for example CAPM alpha. $\mathbf{X}_{pft}$ represents control variables which are the same in equation 2. Firm and year fixed effects are also included.

To estimate the model, we exclude the dummy variable for $i = 3$ and $j = 3$. By excluding it, the b_{ij} represents the percentage flows to a fund in quantile i and j based on fund net return and other return measures, respectively, relative to a fund that was in the third quantiles on both performance measures. Investors use net returns to direct their flows if the sum of these differences for all i and j such that $i > j$:

$$\text{Sum} = \sum_{i>j}^{5} \sum_{j=1}^{4} b_{i,j} - b_{j,i} \tag{8}$$

is significantly greater than zero.

Table 3 reports the sum of coefficients for the horse races between the return model and the others. The results show that investment flows to funds that have higher unadjusted returns instead of higher CAPM alpha, 4-factor alpha, or Morningstar returns. In addition, for each horse race, we calculate the fraction of positive coefficient differences ($b_{i,j} - b_{j,i}$) and conduct the hypothesis test that the fraction equals 50%. The results show that these coefficients are positive 90-100% of the time. Therefore, our pairwise comparison results are not driven by some extreme estimates of coefficients.

[Insert Table 3 near here]

3.3 Top-ranked and bottom-ranked funds

This section provides evidence that investors follow returns, using a non-parametric approach developed in Ben-David et al. (2019). Within each plan, we rank funds by unadjusted returns, the CAPM alpha, 4-factor alpha, and Morningstar return into quintiles, respectively. We then compare flow differences between the top and the bottom quintile funds. Specifically, we examine whether the difference in performance ranking can explain the fraction of funds with positive flows, flows in percentage point, and flows in dollars.

The result is shown in Table 4. Consistent with previous results, the unadjusted return has the most explanatory power for fund flow in both percentage points and dollars. For example, the difference in percent flows between the top and bottom return quintiles is 0.75%, which is statistically significantly higher than 0.58% for Morningstar quintiles, or 0.47% for the CAPM alpha quintiles. Morningstar rating has the most power in explaining the direction of flows. The difference in the fraction of positive flow between the top and bottom Morningstar quintiles is 7.50%, which is marginally higher than 6.25% for unadjusted return, with 10% level of significance.

[Insert Table 4 near here]

3.4 Mean-variance portfolio

We have shown that investors follow raw returns when making investment decisions. Chasing unadjusted-returns is not irrational if investors maximize their expected utility given their belief. To test this hypothesis, we assume that employees in each plan as a representative agent with a mean-variance utility function. Given his/her assets in place from the prior year, the agent chooses the best asset allocation at each year to maximize the utility or sharp ratio of the portfolio.

Formally, employees at firm p in year t allocate their capital to each fund f with proportion of wealth $\mathbf{w}'_{pt} = [w_{f_1}, w_{f_2}, ..., w_{f_{N_{pt}}}]_t$, where N_{pt} is the number of funds that are in firm p's 401(k) plan. Their optimal allocations for next period $t+1$ are the solutions of:

$$\max_{\mathbf{w}_{p,t+1}} \frac{\mathbf{w}'_{p,t+1} E_t[R^e_{p,t+1}]}{\mathbf{w}'_{p,t+1} \mathbf{\Sigma}_{p,t+1|t} \mathbf{w}_{p,t+1}} \tag{9}$$

$$\text{st: } \mathbf{1}'\mathbf{w}_{p,t+1} = 1, \tag{10}$$

$$\mathbf{w}_{p,t+1} \leq (1+b)\mathbf{w}_{pt}, \tag{11}$$

$$\mathbf{w}_{p,t+1} \geq \max\{(1-b)\mathbf{w}_{pt}, 0\}, \tag{12}$$

where $\mathbf{1}$ is vector of 1, and b is boundary constraint obtained from historical cross sectional and time series distribution of the changes in allocations.

The expected returns in excess of risk-free rate $E_t[R^e_{p,t+1}]$ and the conditional covariance of returns $\mathbf{\Sigma}_{p,t+1|t}$ are estimated under different investor's belief or utilization, i.e., unadjusted return, the CAPM alpha, or 4-factor alpha. Under this belief, the excess returns will follow either:

- Net return: $$R^e_{f,t+1} = \frac{1}{36}\sum_{j=0}^{35} R^e_{f,t-j} + \varepsilon_{f,t+1}, \tag{13}$$

- CAPM or 4Factor: $$R^e_{f,t+1} = a_{ft} + \mathbf{F'_{t+1}}\boldsymbol{\beta}_{ft} + \varepsilon_{f,t+1}, \tag{14}$$

where $\varepsilon_{f,t+1}$ has a conditional normal distribution that has mean zero and conditional variance $\sigma^2_{f,t+1}$, or $\varepsilon_{f,t+1}|_{I_t} \sim N(0, \sigma^2_{f,t+1})$. The variance $\sigma^2_{f,t+1}$ follows GARCH(1,1):

$$\sigma^2_{f,t+1} = w_{1f} + w_{2f}\varepsilon^2_{ft} + w_{3f}\sigma^2_{ft}. \tag{15}$$

The conditional covariance of returns of all funds in plan p in year t are defined as follows:

$$\mathbf{\Sigma}_{p,t+1|t} = \mathbf{D}_{p,t+1|t}\mathbf{Q}_{p,t+1|t}\mathbf{D}_{p,t+1|t}, \tag{16}$$

where $\mathbf{Q}_{p,t+1|t}$ is the correlation matrix estimated using past 36 months of fund return data, and $\mathbf{D}_{p,t+1|t}$ is the diagonal matrix with the standard deviation $\sigma_{f,t+1}$ along the diagonal.

Under each model, for all funds f in firm p's 401(k) plan at year t we estimate conditional expected excess returns and covariance matrix using past 36 months of return data. Then, the expected excess returns are:

- Net return: $$E_t[R^e_{f,t+1}] = \frac{1}{36}\sum_{j=0}^{35} R^e_{f,t-j}, \tag{17}$$

- CAPM and 4Factor: $$E_t[R^e_{f,t+1}] = E_t[\mathbf{F}'_{t+1}]\hat{\boldsymbol{\beta}}_{f,t}, \tag{18}$$

where the expected factor retuns $E_t[\mathbf{F}_{t+1}] = \frac{1}{36}\sum_{j=0}^{35}\mathbf{F}_{t-j}$, and conditional covariance matrix $\mathbf{\Sigma}_{p,t+1|t} = \hat{\mathbf{D}}_{p,t+1|t}\hat{\mathbf{Q}}_{p,t+1|t}\hat{\mathbf{D}}_{p,t+1|t}$.

Given the estimated expected returns and covariance of returns along with prior allocations from last year, the employees maximize their utility in equation 9 to obtain the optimal portfolio. We then compare the distance between the realized asset allocation and the holding of optimal portfolio using these two metrics: [1] Δ_{pt} is the average of the absolute difference between the optimal allocations (w^{Model}_{pkt}) and the realized ones (w^{Actual}_{pkt}), and [2]

D_{pt} is the distance between them :

$$\Delta_{pt}^{model} = \frac{1}{N_{pt}} \sum_{k=f_1}^{f_{N_{pt}}} \left| w_{pkt}^{Model} - w_{pkt}^{Actual} \right|, \tag{19}$$

$$D_{pt}^{model} = \sqrt{\sum_{k=f_1}^{f_{N_{pt}}} \left(w_{pkt}^{Model} - w_{pkt}^{Actual} \right)^2}. \tag{20}$$

To estimate the optimal allocations, we use three different boundary constraints 8%, 20%, and 40%, which are obtained from the historical observations of the absolute change in allocations over the years. These numbers are at 25^{th}, 50^{th}, and 75^{th} percentile of the distribution. Under each boundary constraint, Panel 1 in Table 5 shows that the averages of the absolute difference between the realized holdings and the optimal holdings estimated using net return model range from 2.82% to 5.36%. The difference is significantly smaller than those using other models. Panel 2 provides the results for the distance between the vector of realized allocations and that of optimal ones. Regardless of boundary constraints, optimal allocations using net return is significantly closer to the realized ones than using other models. Therefore, the result suggests that the observed asset allocation decisions are consistent with investors belief of unadjusted returns serving as the ranking criteria.

[Insert Table 5 near here]

3.5 Welfare lost

Having documented that investors blindly follow unadjusted returns, we show that investors give up substantial capital gains without at least adjusting for market exposure. For each firm-year panel, we bootstrap hypothetical flows, assuming that investors direct flows based on the CAPM alpha rather than unadjusted returns. We then compare cumulative performances of the observed asset allocation, the hypothetical asset allocation, and the S&P 500 index.

Specifically, we assume that investors chase the CAPM alpha as follows:

$$Flow_{pft} = \beta_0 \alpha^{CAPM}_{f,t-1} + \mathbf{X'}_{pft}\boldsymbol{\beta}_1 + \mu_t + \gamma_p + \epsilon_{pft}, \tag{21}$$

then we simulate the hypothetical investment amount V^s_{pft} to fund f that belongs to plan p in year t by, first, running the residual-resampling bootstrap of equation 21 to simulate the percentage flow $Flow^s_{pft}$ for each fund-plan. Second, the percentage flow is converted to the dollar flow and added to the growth of fund asset ($= V^s_{pf,t-1}(1 + R_{ft})$) to obtain the simulated hypothetical investment amount. We then aggregate the hypothetical allocation and compute their cumulative performances over the sample period. We repeat these procedures 1000 times.

Figure 1 shows the cumulative performances of realized asset allocation and S&P 500 index and the average of those of hypothetical asset allocation over the sample period. We can see that the realized asset allocation underperforms the hypothetical one based on the CAPM alpha ranking by 11% or 2.2 billion dollars.[6] The result suggests that investors can benefit from taking into account the market exposure when evaluating fund performance. The seemingly small magnitude of the difference is due to the fact that, the dollar amount of assets in place is much larger than the dollar amount of flows, which drives down the performance difference between realized flows and hypothetical flows.

Furthermore, both realized and hypothetical asset allocations underperform the S&P 500 index fund, which is commonly available to DC plans. Our results suggest that unsophisticated investors can better off by avoiding active investing and focusing on the market index funds.

[Insert Figure 1 near here]

[6] The difference is significantly at 1% level. Results are similar if we assume that investors chase 4-factor alpha or Morningstar ranking.

4 Aggregated Flow Analysis

To reconcile the difference between our micro-level results and the results in the literature (Barber et al. (2016), Berk and Van Binsbergen (2016)), we aggregate our data at the fund level and re-examine the flow-performance relation. Specifically, the total flow of new money to fund f from all 401(k) plans in year t is

$$AGGflow_{ft} = \frac{V_{ft} - V_{f,t-1}(1 + R_{ft})}{V_{f,t-1}}, \tag{22}$$

where $V_{ft} = \sum_{p \in \Omega_{ft}} V_{pft}$ is the total investment value to fund f from employees of all firms in year t. We then run the following panel regression of aggregated flow of fund f in year t on performance measures in year $t-1$, controlling for fund characteristics and time fixed effects.

$$AGGflow_{ft} = \delta_0 PERF_{f,t-1} + \mathbf{Z'}_{ft}\boldsymbol{\delta} + \mu_t + \eta_{ft}, \tag{23}$$

where $\mathbf{Z'}_{ft}$ represents fund characteristics which are fund expense ratio, fund turn over, logarithm of total fund net assets, and standard deviation of fund returns.

The results are shown in Table 6. The first four columns show that aggregated flows respond to each of the four performance metrics. Column (5) runs a horse-race among all performance measures, and only the CAPM alpha is positive and significant, which is consistent with the prior literature (Barber et al. (2016), Berk and Van Binsbergen (2016)). Our results also alleviate the concern that the difference between our micro-level results and findings in the literature is driven by sample selections.

[Insert Table 6 near here]

Why do aggregated flows respond to the CAPM alpha, while the micro-level flows respond to the unadjusted returns? We conjecture that the inconsistency is driven by different weighting schemes. In particular, the micro-level evidence suggests that the "average" employee in the firm allocate the savings by following unadjusted returns, and the analysis effectively puts more weight on firms with small plan size. The aggregated analysis, on the contrary, puts more weight on firms with large plan size. To reconcile the differences in results between ours and prior literature, we offer a potential explanation through the wealth inequality channel. In particular, we hypothesize that a small proportion of employees possess a substantial portion of savings, and their investment decision follows the CAPM alpha.

To test the hypothesis, we rank firms by the average savings per employee of the plan into quartiles. For each quartile, we re-run the micro-level panel regression of flows on performance measures. The results are shown in Table 7. Almost all quartiles show flow-return relation, except for the highest savings quartile, where flows only respond to the CAPM alpha.

[Insert Table 7 near here]

To see why the highest savings subsample exhibits flow-alpha relation, we compare characteristics of subsamples in Table 8. Specifically, we examine the plan size, savings per employees, the number of employees in each firm, and the firm age since IPOs. The average plan size of the highest savings groups is $1,510 million, while that of the other groups is significantly smaller. The highest savings group also has significantly less number of employee. In fact, this group represents only 14% of the population in our sample but holds more than 51% of the savings. In addition, these employees save on average $183,522 per employee, which is over ten times greater than those in the lowest savings group.

[Insert Table 8 near here]

The massive difference in savings in the 401(k) cannot be attributed to either firms' contribution matching policy or working tenures. First, firms can only match up to 100% of an employee's contribution. However, the highest savings group hold more than ten times the wealth than the lowest savings group. Such the gap cannot be entirely attributed to the difference in firm's matching policies.

Second, the saving gap is not driven by long working tenures of the highest savings group. To address this, we use the difference in firm ages as a proxy for the difference in working tenures between the highest and lowest savings groups. The average difference in firm ages between the two groups is about ten years, and the difference in savings is \$0.17 million. If the difference in firm ages explains the saving gap, employees have to earn an annual wage of \$147,920. However, the income per capita in the U.S. is \$46,550 in 2016, suggesting that the savings gap is unlikely to be contributed to the difference in tenures.[7] Furthermore, the ten years gap in firm ages is likely to overestimate the actual tenure gap, making tenure gap even more unlikely to explain the savings gap. According to the Department of Labor, the median tenure of workers with age from 55 to 64 is 10.3, whereas that of younger workers with age from 25 to 34 is 2.8 as of 2016.[8] Consider an extreme case, in which the firm in the highest savings group is full of workers with age between 55 and 64, and the firm in the lowest savings group is full of workers with age between 25 and 34. Then the tenure gap between the two extreme firms is only 7.5, which is smaller than the firm age difference. Therefore, the saving gap is unlikely to be explained by the firm age difference.

We also infer employee ages from the name of the Target Date Funds, which typically contains the year of retirement, and use the difference in employee ages as a proxy for the difference in working tenures. We then show that the difference in employee ages cannot explain the savings gap. Specifically, let a target date fund f have a targeted utilization year of T_f. We assume that if employees in year t invest in this fund, they will retire around year T_f. Therefore, the average age of employees who invest in this target date fund f in year t is:

$$Age_{pft}^{TA} = 65 - (T_f - t) \tag{24}$$

Panel 1 in Table 9 shows that the difference in employee age between the highest and lowest savings groups is 1.1 years if only target date funds are used. Next, we then predict the

[7] Data is from The Census Bureau https://www.census.gov/data/tables/time-series/demo/income-poverty/cps-pinc/pinc-01.html.

[8] Data is from https://www.bls.gov/news.release/tenure.t01.htm.

average age of employees (denote Age^{NT}_{pft}) of firm p who invest in non-target date fund f in year t using the model as follows:

$$Age^{O}_{pft} = \Phi\Big(\mathbf{N'}_{pft}\boldsymbol{\beta} + \mu_t + \gamma_p\Big) + \zeta_{pft}, \tag{25}$$

where

$$Age^{O}_{pft} = \frac{Age^{K}_{pft} - 22}{65 - 22} \in (0, 1), \tag{26}$$

and $K = \{TA, NT\}$; $\Phi(.)$ is the cumulative distribution function of the standard normal distribution, and ζ_{pft} is normally distributed with zero mean. $\mathbf{N}_{pft}$ represents fund control variables which are the fraction of investment in plan asset, the logarithm of total fund net assets, expense ratio, fund turn over, fund return volatility, and fund's time-varying loading on market, size, and value factors. Panel 2 in Table 9 shows that the model has high prediction power, the pseudo R^2 is 94%. Accounting for predicted ages, the difference in employee age between the highest and lowest savings groups is 2.3 years, which is clearly not a main contribution to the difference in savings.

[Insert Table 9 near here]

To sum up, we demonstrated that the firm's contribution policy or employees' working tenures cannot explain the savings gap. We argue that the difference in the savings gap is driven by the difference in employees' participation rate and wages. Participation rate ranges from zero to 6%, and employees can decide their preferred rate. A high participation rate implies that employees are comfortable investing, which presumably indicates some level of financial sophistication. A high wage implies that employees are probably more skilled or have higher education degrees, which also correlates with financial sophistication. As a result, the saving gap is due to different levels of financial sophistication, which explains that the high-savings group selects funds based on the CAPM alpha.

5 Conclusion

This paper studies how investors allocate wealth with a limited choice. Prior literature debates on whether investors adjust returns for risk exposures (Barber et al. (2016), Berk and Van Binsbergen (2016)), or rely on third-party signals (Ben-David et al. (2019), Evans and Sun (2018)). Instead of treating all market participants as a representative agent with unlimited attention, who can browse through all funds and make investment decisions, we re-examine this question at the micro level, where investment options are naturally bounded. Using our hand-collected dataset on a large sample of defined contribution plans, we show that most investors blindly follow unadjusted returns within their limited choice. The result is disconcerting given that a large portion of pension assets is in 401(k). Our paper has important implications to plan sponsors and investors. From the sponsors' perspective, it is necessary to offer a diversified set of funds to their employees. More importantly, sponsors can hold educational workshops, so that employees can better understand trade-offs between risk and return. It will also improve the stability of the plan when the market becomes volatile. From the employees' perspective, they are better off to hold a well-diversified index fund, rather than chasing high past returns.

Our paper also contributes to the flow-performance relation literature, and points out the lack of financial literacy in the workplace. We show that, while 86% of investors in our sample allocate their savings by following unadjusted returns, the remaining 14% invest according to the CAPM alpha. Moreover, those who chase CAPM alpha holds 51% of the wealth, which tilts results towards the findings of Barber et al. (2016), and Berk and Van Binsbergen (2016).

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Figure 1
Cummulative performance of 401(k) plans

The figure shows the cumulative performance of 401(k) plans. The blue long dash line plots the cumulative returns of S&P 500. The black dash line represents the cumulative returns of the 401(k) plans in our sample. We also bootstrap hypothetical flows to provide a counterfactual scenario, in which investors follow the CAPM alpha ranking. The red solid line shows the average cumulative returns of the hypothetical 401(k) plans over 1000 simulations.

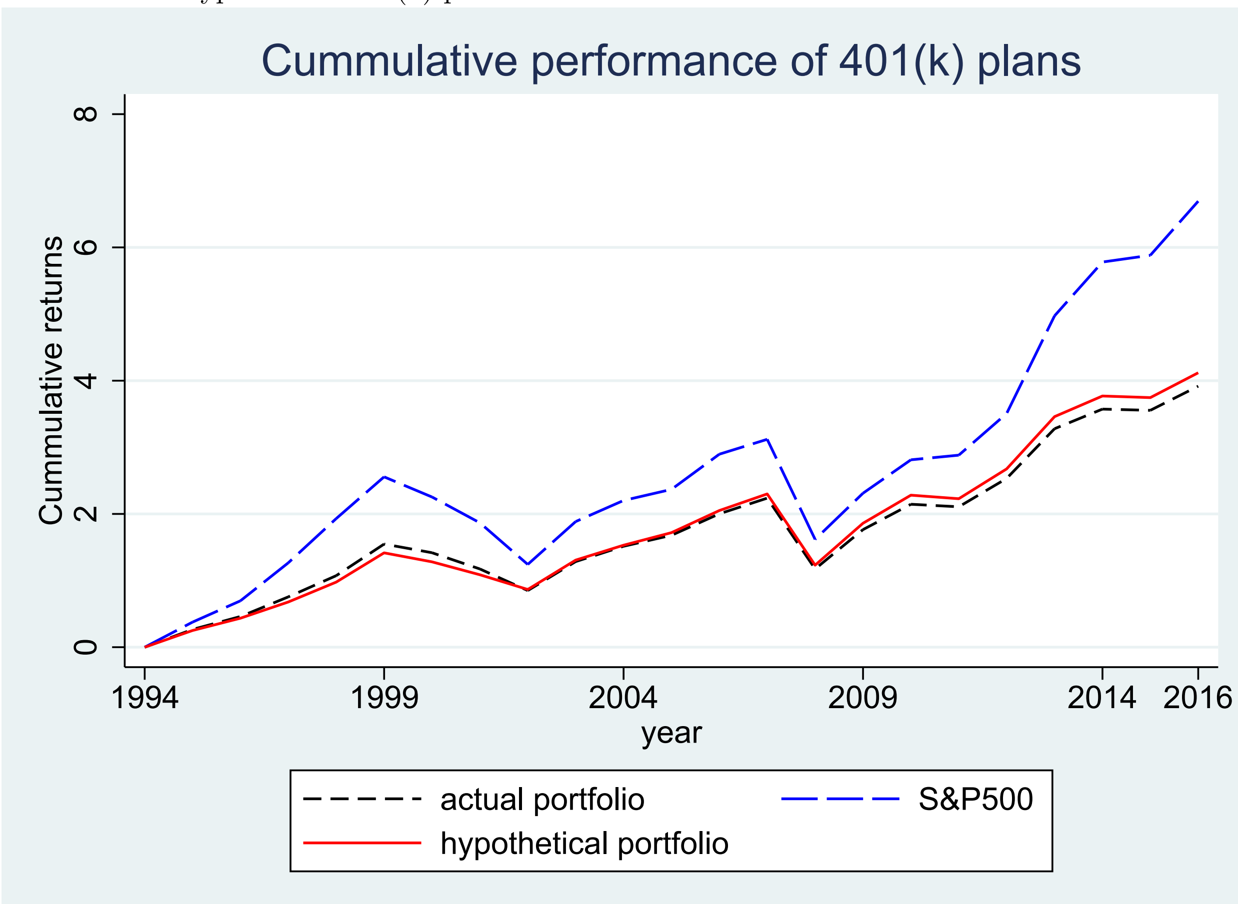

Table 1
Summary statistics

This table reports the descriptive statistics for our sample. Column 1 reports the number of firms with 401(k) plan. Columns 2 and 3 the average and median value of plan size in millions. Column 4 reports the proportion of company stock held by the employees in their saving. Columns 5 and 6 shows the total number of mutual funds that are invested in all plans and the average number of funds used in each plan, respectively. Columns 7 and 8 report the the average fraction of capital investments in equity funds and bond funds to the total investment in mutual funds within a plan.

Year	Number of firms	Plan size (millions)		Company stock share (%)	Number of funds	Number of funds per plan	% investment in	
		Mean	Median				equity funds	bond funds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1993	90	504	109	81.86	110	3	60.24	22.71
1994	160	651	91	80.36	167	3	58.90	27.49
1995	244	378	75	78.73	242	3	58.70	27.67
1996	317	412	74	78.65	325	4	61.88	26.10
1997	404	466	78	76.96	435	4	64.76	23.46
1998	476	468	83	74.23	550	5	66.68	21.91
1999	528	496	106	71.97	722	6	71.24	18.41
2000	601	508	95	71.85	858	7	72.87	17.39
2001	683	424	95	72.62	1,022	8	67.73	21.09
2002	740	401	84	72.30	1,142	9	62.70	25.36
2003	812	553	112	72.21	1,304	10	67.19	21.93
2004	834	657	133	71.67	1,390	10	70.19	18.68
2005	810	717	157	71.16	1,438	11	71.87	17.58
2006	779	829	189	70.79	1,427	11	72.44	17.14
2007	768	926	203	70.01	1,447	12	71.45	16.77
2008	740	674	149	70.60	1,450	13	62.27	24.31
2009	724	800	183	70.30	1,424	13	63.81	22.48
2010	682	982	231	69.43	1,425	14	65.04	20.56
2011	668	1,003	261	69.48	1,437	15	62.43	21.46
2012	640	1,187	316	69.14	1,426	15	62.14	21.05
2013	611	1,476	387	69.27	1,612	16	67.14	16.46
2014	586	1,518	412	69.07	1,671	17	67.78	15.21
2015	542	1,449	403	68.24	1,621	17	68.05	14.71
2016	475	1,606	471	70.50	1,163	14	68.02	14.51

Table 2
Flow-performance relation at firm-fund level

This table reports results from regressions of flows at firm-fund level in year $t+1$ on fund performance, plan and fund characteristics in year t. There are four different measures of fund performance: [1] *Net return*$_t$ is fund return net of fee, [2] α_t^{CAPM} is fund abnormal return which is adjusted for CRSP value-weighted stock index (market) factor for equity and balanced funds and adjusted for the U.S. aggregate bond index for bond funds, [3] $\alpha_t^{4Factor}$ is fund abnormal return which uses the Carhart (1997) four-factor model for equity and balanced funds, and four-bond-factor for bond funds, following Ma et al. (2019), Cici and Gibson (2012), and Elton et al. (1995), and [4] *MStar return*$_t$ is Morningstar risk-adjusted return. Plan characteristics include logarithm of the number of funds, firm return, and firm stock flow to 401(k) plan. Fund characteristics include expense ratio, turn over, the logarithm of total fund net assets, and fund return volatility. Standard errors are two-way clustered at the firm and year level. t-statistics are in brackets and *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$
Net return$_t$	0.021**				0.017**	0.022**	0.019**	0.018**	0.021**
	[2.71]				[2.41]	[2.54]	[2.67]	[2.53]	[2.60]
α_t^{CAPM}		0.023**			0.007			0.016	0.014
		[2.39]			[0.96]			[1.63]	[1.45]
$\alpha_t^{4Factor}$			0.016*			-0.004		-0.015	-0.017*
			[2.00]			[-0.54]		[-1.61]	[-1.95]
MStar return$_t$				0.020**			0.005	0.003	0.007
				[2.19]			[0.70]	[0.59]	[1.20]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Invt. type FE	No	No	No	No	No	No	No	No	Yes
Observations	119,307	119,307	119,307	119,307	119,307	119,307	119,307	119,307	119,307
Adjusted R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Table 3
Pairwise model horse race

This table reports the pairwise horse-race between net return model and the other competing models. We estimate the relation between flows and a fund's quintile ranking based on their performance metrics within the firm by running the following regression:

$$Flow_{pft} = \sum_i \sum_j b_{ij} D_{ijpft} + \mathbf{X'}_{pft}\mathbf{c} + \mu_t + \gamma_p + \epsilon_{pft},$$

where D_{ijpft} is a dummy variable that equals one if fund f of firm p in year t is in quantile i based on the fund net return and quantile j based on other performance measures. To estimate the model, we exclude the dummy variable for $i = 3$ and $j = 3$. The matrix $\mathbf{X}_{pft}$ represents firm and fund control variables, which are the same set of controls in Table 2. μ_t and γ_p are year and firm fixed effects. This table reports the sum of the differences between coefficients b_{ij} and b_{ji} for all i and j such that $i > j$:

$$\text{Sum} = \sum_{i>j}^{5} \sum_{j=1}^{4} b_{i,j} - b_{j,i}.$$

t-statistics are in brackets and **, *** indicate significance at the 5%, and 1% levels, respectively.

Winning Model	Net return	Net return	Net return
Losing Model	CAPM	4Factor	MorningStar
Sum of coefficient differences	0.019^{***}	0.029^{***}	0.015^{***}
	[4.83]	[7.94]	[4.74]
% of coefficient differences > 0	90^{**}	100^{***}	90^{**}
Binomial p-value	(0.021)	(0.002)	(0.021)

Table 4
Flows to top-ranked versus bottom-ranked funds

Table reports the average fund flows to the best and worst performing funds. Specifically, for each firm at each year, we rank funds within the plan by various performance measures into quintiles. Top quantile and bottom quantile have the best and the worst performing funds. *Positive Flows* is the fraction of funds with positive flows. *Flows* and *Dollar Flows* are flows as a fraction of plan size and dollar flows, respectively. The paired tests of the Diff (= Top - Bottom) between "Net return" quantiles and other quantiles are represented by *, **, *** indicating significance at the 10%, 5%, 1% levels, respectively.

	Positive Flows (%)			Flows (%)			Dollar Flows (thousands)		
	Top	Bottom	Diff	Top	Bottom	Diff	Top	Bottom	Diff
Net return	67.14	60.89	6.25	1.44	0.69	0.75	839.48	243.61	595.86
CAPM	65.79	60.54	5.25**	1.23	0.75	0.47***	645.81	258.59	387.23***
4Factor	65.02	62.49	2.54***	1.16	0.81	0.35***	570.43	314.15	256.28***
MorningStar	67.16	59.66	7.50*	1.34	0.75	0.58**	712.54	260.06	452.48**

Table 5
Distance to mean-variance portfolios

This table reports the average of the absolute difference (Δ_{pt}) and the distance (D_{pt}) between the optimal allocation (w_{kpt}^{Model}) and firm's realized holding (w_{kpt}^{actual}):

$$\Delta_{pt}^{model} = \frac{1}{N_{pt}} \sum_{k \in \Omega_{pt}} \left| w_{kpt}^{Model} - w_{kpt}^{actual} \right|, \quad D_{pt}^{model} = \sqrt{\sum_{k \in \Omega_{pt}} \left(w_{kpt}^{Model} - w_{kpt}^{actual} \right)^2}$$

where Ω_{pt} is the set of all funds in firm p at year t. The optimal allocation is the solution of

$$\max_{\mathbf{w}_{p,t+1}} \frac{\mathbf{w}'_{p,t+1} E_t[R^e_{p,t+1}]}{\mathbf{w}'_{p,t+1} \mathbf{\Sigma}_{p,t+1|t} \mathbf{w}_{p,t+1}}$$
$$\text{st: } \max\{(1-b)\mathbf{w}_{pt}, 0\} \leq \mathbf{w}_{p,t+1} \leq (1+b)\mathbf{w}_{pt}, \text{ and } \mathbf{1}'\mathbf{w}_{p,t+1} = 1,$$

where $\mathbf{w}_{p,t+1}$, $R^e_{p,t+1}$, and $\mathbf{\Sigma}_{p,t+1|t}$ are vectors of allocations, returns in excess of risk-free rate, and conditional covariance of returns of all funds that belongs to firm p's 401(k) plan in year $t+1$; b is boundary constraint obtained from historical distribution of the changes in allocations. Under each model, ie. net return, CAPM, or 4-factor models, the optimal allocations are estimated with different values of conditional expected excess returns and covariance of returns. Section 3.4 provides detailed estimation procedures. The following tables also report the pair tests between Net return model and the others. The p_values of the pair tests are in parentheses and the standard errors are clustered at the firm level. All numbers are in percentage.

Panel 1: Average difference (Δ_{pt}^{Model})

Boundary constraint (b)	Net return	CAPM	4Factor
40 (75pct)	5.36	5.45	5.54
		(0.1)	(0.1)
20 (50pct)	3.56	3.62	3.67
		(0.1)	(0.1)
8 (25pct)	2.82	2.85	2.88
		(0.1)	(0.1)

Panel 2: Average distance (D_{pt}^{Model})

Boundary constraint (b)	Net return	CAPM	4Factor
40 (75pct)	17.55	17.85	18.12
		(0.1)	(0.1)
20 (50pct)	11.66	11.85	11.99
		(0.1)	(0.1)
8 (25pct)	9.16	9.24	9.30
		(0.1)	(0.1)

Table 6
Flow-performance relation at aggregate level

This table reports results from regressions of aggregated flows at fund level in year $t+1$ on fund performance and fund characteristics in year t. The aggregated flow of new money to fund f from all 401(k) plans in year t is defined as follows:

$$AGGflow_{ft} = \frac{V_{ft} - V_{f,t-1}(1 + R_{ft})}{V_{f,t-1}},$$

where $V_{ft} = \sum_{p \in \Omega_{ft}} V_{pft}$ is the total investment from all firms in year t, and R_{ft} is fund return. Fund performance and fund characteristics are described in Table 2. Standard errors are clustered at the year level. t-statistics are in brackets and *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) $AGGflow_{t+1}$	(2) $AGGflow_{t+1}$	(3) $AGGflow_{t+1}$	(4) $AGGflow_{t+1}$	(5) $AGGflow_{t+1}$
Net return$_t$	0.183***				0.031
	[4.76]				[0.31]
α_t^{CAPM}		0.359***			0.430**
		[6.75]			[2.38]
$\alpha_t^{4Factor}$			0.250***		-0.148
			[4.38]		[-1.24]
MStar return$_t$				0.224***	0.027
				[3.29]	[0.21]
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	21,642	21,642	21,642	21,642	21,642
Adjusted R^2	0.03	0.03	0.03	0.03	0.03

Table 7

Flow-performance relation at firm-fund level by employee saving

This table reports results from regressions of flows at firm-fund level in year $t+1$ on fund performance, plan and fund characteristics in year t. Fund performance, plan and fund characteristics are described in Table 2. For each year, we create quartiles of firm's average 401(k) investment per employee. *Low* and *High* contain firms with the lowest and highest investment per employee, respectively. Standard errors are clustered at the firm and year level. t statistics are in brackets and *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

401(k) saving/employee	Low	2	3	High
	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$
$Net\ return_t$	0.027**	0.021**	0.019***	0.009
	[2.37]	[2.22]	[3.00]	[1.46]
α_t^{CAPM}	0.006	0.010	0.014	0.031**
	[0.36]	[0.84]	[1.64]	[2.28]
$\alpha_t^{4Factor}$	-0.024	-0.004	-0.015*	-0.018
	[-1.49]	[-0.32]	[-1.73]	[-1.66]
$MStar\ return_t$	0.029*	0.007	-0.005	-0.008
	[1.90]	[0.81]	[-0.65]	[-1.12]
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	25,633	28,802	30,111	33,945
Adjusted R^2	0.29	0.24	0.22	0.10

Table 8
Plan and employee characteristics

This table reports the summary statistics on employee's 401(k) investment. Firms are sorted by firm's average 401(k) investment per employee, which are described in Table 7. Table also reports the difference in mean tests for plan size and number of employee between the highest savings group and the others. The standard errors are clustered at the year level. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

401(k) saving/employee		Low	2	3	High
Plan size (in millions):					
- include company stock	-Average	370***	392***	871***	1,510
	-Median	81	106	199	450
- exclude company stock	-Average	100***	109***	208***	344
	-Median	19	27	46	109
Savings per capita:					
- include company stock	-Average	13,121	38,079	69,106	183,522
	-Median	10,594	37,037	65,332	140,466
- exclude company stock	-Average	3,585	10,898	19,383	50,702
	-Median	2,403	9,926	17,509	37,805
Savings per capita per fund	-Average	516	1,330	2,377	5,800
	-Median	366	1,139	2,061	3,977
Number of employee	-Average	37,220***	10,735**	12,029***	9,189
	-Median	10,800	3,277	3,392	3,244
Firm age	-Average	24.0	22.6	25.2	33.6
	-Median	18.0	19.0	21.0	30.0

Table 9
Employee age

Panel 1 reports average ages of employees who invested in target date funds. The average ages of those who invested in non-target date funds are estimated using the model as follows:

$$Age^{O}_{pft} = \Phi\left(\mathbf{N'}_{pft}\boldsymbol{\beta} + \mu_t + \gamma_p\right) + \zeta_{pft},$$

where $Age^{O}_{pft} = \frac{Age_{pft}-22}{65-22} \in (0,1)$, $\Phi(.)$ is the cumulative distribution function of the standard normal distribution, ζ_{pft} is normally distributed with zero mean, and $\mathbf{N}_{pft}$ represents fund control variables. *Fund weight* is the fraction of investment in fund f within 401(k) plan p in year t. β_{MKT}, β_{SMB}, β_{HML} are fund's time-varying loading on market, size, and value factors. μ_t and γ_p are year and firm fixed effects. Panel 2 reports the coefficients from the employee age prediction. Standard errors are clustered at the year level and *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel 1: Average age.

401(k) saving/employee	Low	2	3	High
Age from target date funds	48.6	49.2	49.3	49.7
Observations (firm-year)	635	728	751	894
Age from target date funds + prediction model	44.1	45.7	45.4	46.4
Observations (firm-year)	1,400	1,435	1,475	1,594

Panel 2: Age prediction.

	Coefficients	t_stat
Fund weight	1.10***	[5.64]
Fund weight^2	−2.56***	[−4.61]
Fund Size	−0.42***	[−3.95]
Fund Size^2	0.04***	[6.54]
Expense Ratio	1.25***	[4.03]
Expense Ratio^2	−0.89***	[−3.93]
Turnover Ratio	0.10*	[1.95]
Fund Return Volatility	−0.55	[−0.09]
β_{MKT}	−5.06***	[−14.01]
β_{SMB}	−0.94**	[−2.15]
β_{HML}	−0.04	[−0.08]
Firm FE	Yes	
Year FE	Yes	
Observations	16,179	
Pseudo R^2	0.94	