FINANCIAL
SERVICES
REVIEW

Financial Services Review 25 (2016) 51–72

The overlooked momentum traders in 401(k) plans

Ning Tang[a,*]

[a]*Department of Finance, College of Business Administration, San Diego State University, 5500 Campanile Drive, SSE 3306, San Diego, CA 92182-8236, USA*

Abstract

Using a unique dataset on over one million 401(k) traders, we investigate momentum trading in 401(k) plans. We identify momentum traders in each quarter and evaluate how these traders perform. Results indicate the existence of momentum traders. However, there is no evidence that they successfully improve their portfolio performance. Instead, momentum sellers sell the outperformed funds. Overall, momentum traders could lose up to 2.14% per year. In seeking to explain such losses, we observe that 401(k) momentum traders follow a naïve momentum strategy. They do not have the ability to select funds with momentum investing styles but, instead, simply chase past returns.

JEL classification: G11; G12; G23

Keywords: Pension fund management; Momentum; Trading; Portfolio performance; 401(k) plan

1. Introduction

Momentum trading is a trading strategy whereby investors buy past winners and sell past losers. Numerous studies point out that a hypothetical investor who follows momentum trading strategy can generate significant positive returns in the short term (see, e.g., Jegadeesh and Tittman, 1993, 2001; Rouwenhorst, 1998). Performance persistence in mutual funds further confirms the possibility of realizing abnormal return by chasing past winner funds (Goetzmann and Ibbotson, 1994; Grinblatt and Titman, 1992; Hendricks et al., 1993).

Acknowledgement: This research is supported by the University Grants Program at San Diego State University. The author also acknowledges Vanguard for providing recordkeeping data under restricted access conditions and support from the Pension Research Council at The Wharton School. The author thanks Olivia S. Mitchell, Stephen P. Utkus, Marie-Eve Lachance, and S. G. Badrinath for helpful comments.

* Corresponding author. Tel.: +1-619-594-2082; fax: +1-619-594-3272.
E-mail address: ntang@mail.sdsu.edu

Consequently, many portfolio managers, institutional and individual stock investors, and mutual fund traders subscribe to the view that momentum strategies yield significant profits and follow such strategies (Jegadeesh and Titman, 2001; Grinblatt and Keloharju, 2000; Grinblatt, Titman, and Wermers, 1995; Solomon, Solges, and Sosyura, 2014). In particular, a series of articles have documented a strong positive relation between mutual fund past performance and subsequent fund inflows (see, e.g., Goetzmann and Massa, 2002; Sirri and Tufano, 1998). However, most of previous studies are based on fund level data with all individual traders aggregated. Individual momentum traders were not identified and their performances were not evaluated. Little is known whether individual traders could successfully implement momentum strategy to yield profit in real life. Here we ask whether there exist momentum traders in 401(k) plans and whether they could achieve portfolio performance improvements.

This question fits into the larger question of whether 401(k) traders can improve their 401(k) portfolios by implementing a trading strategy—a question of particular interest to policymakers and plan sponsors who oversee the plans, and to plan participants who will rely on their 401(k) accruals to finance their retirements. If 401(k) participants were able to successfully adopt a trading strategy, such as momentum trading, that would boost their 401(k) balance by the time of retirement, this would not only benefit the economic welfare of individual participants but would also increase soundness and stability of the entire retirement system. However, if momentum trading and other strategies used to improve 401(k) performance do not actually generate gains or even lead to losses, participants need to know this and refrain from adopting such strategies. Without information on how such strategies perform, individuals could end up siphoning off their retirement wealth with inappropriate behavior, while the plans themselves also experience management costs.

Unfortunately, compared with the extensive literature on momentum trading outside retirement accounts (e.g., Pettengill, Edwards, and Schmitt, 2006; Pettengill, Edeards, and Griggs, 2009), momentum traders in 401(k) plans have been largely overlooked. The literature contains little on whether 401(k) traders adopt momentum strategies and how these momentum traders perform. In fact, there are many reasons to suspect that investors may exhibit different behavior when trading with retirement and nonretirement accounts. Studies on mental accounting observe that investors tend to split their investment into a *safe* account, which is designed to maintain wealth level, and a *risky* account, used for speculation; their choices in separate accounts vary (Choi, Laibson, and Madrian, 2007; Rockenbach, 2004). A 401(k) account would be considered a *safe* account, meant for securing retirement wealth, whereas active nonretirement trading accounts would be considered *risky* accounts and meant for speculation. Because active trading accounts and 401(k) plans serve completely different functions, investors may exhibit different behavior when trading with retirement and nonretirement accounts. In fact, literature has shown that 401(k) participants engage in trading infrequently because of inertia, which is sharply different from the excessive trading in discount brokerage accounts (Agnew, Balduzzi, and Sunden, 2003; Tang, Mitchell, and Utkus, 2012); plan sponsors seem not to expect 401(k) plan participants to excel in profitable trading. Several studies have also highlighted the behavioral biases and financial literacy constraints that appear to hinder 401(k) plan participant decision-making. For example, plan participants use naive allocation strategies (Agnew, 2002; Benartzi and Thaler, 2001); exhibit inertia in asset allocation and rebalancing (Agnew et al., 2003; Ameriks and Zeldes, 2004); display inconsistence between objective and subjective assessment of retirement adequacy (Kim and Hanna, 2015), and overinvest in employer stock (Benartzi et al., 2007; Even and Macpherson, 2007; Huberman and Sengmueller, 2004; Liang and Weisbenner, 2002). The presence of these factors could contribute to the difference in trading outcomes in and outside retirement accounts. Hence, it is necessary to study momentum traders in 401(k) plans and examine their performance.

This article adds to the literature by investigating momentum traders and their performance in 401(k) plans. It also explores the causes of inefficiency among 401(k) momentum traders. The unique Vanguard record-keeping dataset on over one million individual traders allows us to study the trading behavior in 401(k) plans at the individual account level. We follow the literature to identify momentum traders in each quarter by binomial test. Our results indicate the existence of a group of traders who follow momentum strategies. However, we find no evidence of performance improvements. On the contrary, momentum sellers lose significantly by selling outperformed funds in certain cases; overall, momentum traders could lose up to 2.14% per year. In investigating why momentum traders in 401(k) plans do not produce gains, we find that these momentum traders aren't able to identify funds with momentum investing styles, and thus don't actually benefit from the momentum effect. Instead, they naively follow past fund performances.

The remainder of the article is organized as follows. Section 2 describes our data and provides descriptive statistics. Section 3 introduces our method of identifying momentum traders. Section 4 shows the performance of momentum traders. Section 5 explains the inefficiency of momentum trading. Section 6 offers discussions on how our findings differ from prior studies and Section 7 concludes.

2. Data

The data underlying this study, provided by the Vanguard group, is a record-keeping dataset of 5,647,728 eligible employees in DC pension plans, mostly 401(k) plans, from January 2005 to December 2010. To demonstrate the representativeness of Vanguard sample, Table 1 Panel A shows the plan level summary statistics as of December 2010. As of December 2010, the whole dataset contained records on over three million employees participating in 2,144 DC plans with a total of $259 billion of assets under management. The data spans 236 four-digit NAICS industries. It is noted that the sample is not a balanced panel since not every participant stayed in the plan during the sample period. Therefore, we observe fewer participants as of December 2010 (3,281,505) than during the whole sample period (5,647,728). VanDerhei et al., (2011) report that in 2010, there were 23.4 million 401(k) plan participants with a total asset value of $1.4 trillion in the U.S. market. These figures are from the EBRI/ICI dataset, which is a representative sample of the estimated universe of 401(k) plans. It implies that Vanguard dataset represents 18% of the asset value and 14% of the participants of the extensive EBRI/ICI dataset.

Table 1 Panel B summarizes participants' characteristics in the whole sample in 2010. The median age of participants in 2010 is 46—very close to the national median participant age of 45 (VanDerhei et al., 2011). The average and median individual account balances are $67,360 and

Table 1 Descriptive plan, participant, and traders statistics

A. Plan characteristics (as of December 2010)		
Number of participants	3,281,505	
Number of plans	2,144	
Total assets under management	$259,090,794,149	
Number of industries	236	
	Mean	Median
B. Participants characteristics (in 2010)		
Male (yes = 1)	58.72%	1
Age	45.57	46
Online 401(k) account registration	64.15%	1
Average individual account balance	$67,360	$20,998
Average individual risk exposure	59.60%	60.00%
C. Trading statistics (January 2005 through December 2010)		
No. of participants	5,647,728	
No. of traders	1,458,037	
No. of equity traders	1,390,392	
Average number of trades per year (among all participants)	0.78	
Average number of trades per year (among traders)	6.16	
Average annual turnover rate (among all participants)	36.24%	
Average annual turnover rate (among traders)	239.51%	
D. Equity traders characteristics (in 2010)		
Male (yes = 1)	63.75%	1
Age	48.55	49
Online 401(k) account registration	90.41%	1
Average individual account balance	$127,778	$64,111
Average individual risk exposure	62.51%	66.97%

Note: The table shows the plan-level summary statistics as of December 2010 in Panel A, individual participant characteristics in 2010 in Panel B, the trading statistics during the sample period January 2005 through December 2010 in Panel C, and individual characteristics in 2010 of those who traded equity assets in Panel D. A participant is considered as a trader if he traded at least once during the sample period; a participant is considered as an equity trader if he traded equity assets including equity and balanced funds at least once during the sample period. We count a buy or sell transaction on a daily basis as one trade. To calculate individual annual turnover rate, we sum the absolute values of trading amount (both buy and sell) in one year and divide this sum by two. We then divide the annual trading amount by the account balance at the beginning of the year.

$20,998, compared with the national average and median account balances of $60,329 and $17,686. The average individual account risk exposure is 59.6%, close to the national average of 62% (VanDerhei et al., 2011). These similarities lead us to believe that the Vanguard data we use here is representative of the overall population of 401(k) participants.

Table 1 Panel C shows trading statistics during sample period January 2005 through December 2010. Out of 5,647,728 participants in the whole sample, around 1.5 million (26% of participants) traded during the six year sample period. Participants in our sample traded 0.78 times per year with an average annual turnover rate of 36.24%.[1] This contrasts sharply with the excessive trading in discount brokerage accounts. For example, Barber and Odean (2000) report a monthly turnover rate of 6% to 7% in their discount brokerage account sample. It is also important to note that, although overall 401(k) trading is limited, investors who do trade, trade a substantial amount. The average number of trades is 6.16 per year and the average annual turnover rate is 239.51% among traders. That is to say that infrequent trading is an unsound argument for disregarding 401(k) participants' trading behaviors. Among those who trade, their choices significantly impact their portfolios.

To study how 401(k) participants reacted to past returns, we select those who traded in equity assets, including equity and balanced funds, between January 2005 and December

2010.[2] In total, 1,390,392 participants traded equity assets and they are included in our final trading sample. For each trader, we record the name and amount of individual funds purchased or sold every month together with the historical monthly fund returns. The data also reflects the funds each plan offered to its participants each month. We also incorporate individual month-end portfolio holdings, which we can use to calculate individual account balances each month.

Table 1 Panel D reports the individual attributes of our selected trading sample on equity traders in 2010. Compared with the results in Panel B, we see that the subsection of participants who trade in their 401(k) plans tend to be affluent older men who use the Internet to access their 401(k) accounts and who tend to be more risk-seeking in their investments than their non-trader counterparts. This confirms previous findings (Agnew et al., 2003; Tang et al., 2012).

3. Momentum traders in 401(k) plans

We follow Goetzmann and Massa (2002) and Agnew et al., (2003) to use individual account activity to classify investors according to their conditional pattern of fund purchases and sells. Momentum buyers (sellers) are defined as those traders who are more likely to buy (sell) funds with past positive (negative) returns (Goetzmann and Massa, 2002). After identifying momentum buyers and sellers, we then study the performance of momentum traders. This implies that our definition of momentum investing is different from the way Jegadeesh and Tittman (1993) apply the term in their profitable momentum strategies. The reason is that the focus of the article is to study the performance of individual momentum traders, instead of the outcome of a hypothetical investing strategy.

Specifically, we follow the literature (Agnew et al., 2003; Goetzmann and Massa, 2002) and adopt binomial test to identify momentum traders. The null hypothesis for an investor to follow momentum buying strategy in a quarter is that the ratio of his purchases with positive returns to total purchases is equal to the percentage of funds with positive returns of all funds available to trade in that quarter. Using a one-tailed binomial test, if the null hypothesis is rejected—that is, if the frequency of positive-return fund purchases is significantly higher than expected from a random distribution—the investor is classified as a momentum buyer. In a similar manner, the null hypothesis for momentum seller is defined as follows:

Buy	$H_0: B_p \sim Binomial\left(B, \frac{N_p}{N}\right)$
Sell	$H_0: S_n \sim Binomial\left(S, \frac{N_n}{N}\right)$

where each individual in each quarter has N funds to trade, of which N_p funds have positive returns and N_n funds have negative returns. In all, he buys B funds, of which B_p have positive returns. He also sells S funds, of which S_n have negative returns. Test results are based on the 1% significance level.

This methodology distinguishes investors who follow certain trading strategies from those who trade randomly. Because the methodology requires information on the investment opportunities available to each investor, few studies have used it because of limitation of the data. Instead, most articles have explored correlations between security flows and their returns or have regressed trades on past asset returns (see, e.g., Grinblatt and Keloharju, 2001; Grinblatt et al., 1995). The problem with such methodologies is that they cannot truly distinguish between feedback and random trading strategies, because positive or negative feedback trading can result from market conditions rather than from any conscious strategic trading.

We analyze investors' trading strategies in buy decisions separately from sell decisions, as people may follow different strategies when they buy versus when they sell (Grinblatt et al., 1995; Sirri and Tufano, 1998). We identify momentum traders quarterly. It is because we found 401(k) traders tend to change their trading strategies through time in our preliminary results; hence it is inappropriate to assume they follow the same strategy in a year or over a longer period and investigate their momentum trading performance during that long period. We do not choose monthly level, as 401(k) plan participants are prone to inertia when rebalancing (Agnew et al., 2003). Therefore, we identify momentum traders quarterly so that we will have sufficient trading data from each individual.

Momentum trading is considered as a short-term (less than one year) strategy. The time interval commonly selected to study momentum strategy ranges from one month to one year (Gruber, 1996; Jegadeesh and Tittman, 1993, 2001; Warther, 1995; Zheng, 1999). In the baseline analysis, we focus on investors' reactions to the past month's return. We assume investors react to past returns without delay, as the momentum effect only exists in the short-term. Specifically, each quarter, we first calculate the number of funds with positive or negative returns one month ago. We then determine if a buyer or a seller follows momentum strategy in response to last month fund return in that quarter using the binomial test. The fund cash flows by momentum traders identified here will be used to construct testing portfolios in the following sections. In the robustness test, we rerun the analysis based on investors' reaction to funds' returns over the past quarter and year (time lag $j = 3$ and 12 months).

Fig. 1 Panel A shows the cumulative number and percentage of traders who follow momentum strategies with various return lags. Specifically, we calculate the total number of momentum buyers and sellers, and the percentage of momentum traders out of all buyers and sellers throughout the testing period (January 2005 through December 2010). Fig. 1 Panel B reports quarterly momentum trading statistics.

First, we establish that each quarter, there does exist a group of alert traders who follow momentum trading in 401(k) plans. For example, as depicted in Fig. 1 Panel A, in reaction to the past month's return, a total of 76% of the 1.15 million buyers adopted momentum strategies at least once during the sample period; Sixty percentage of the 1.04 million sellers sell the previous month's losers, making them momentum sellers at least in one quarter during sample period.[3] Quarterly average statistics in Fig. 1 Pane B show that each quarter, a portion of 58% of buyers followed momentum strategies when evaluated with past month's return; forty percentage of sellers are momentum traders. In addition, we confirm that patterns in buy and sell decisions vary. The momentum strategy is more popular in buy decisions than in sell decisions.

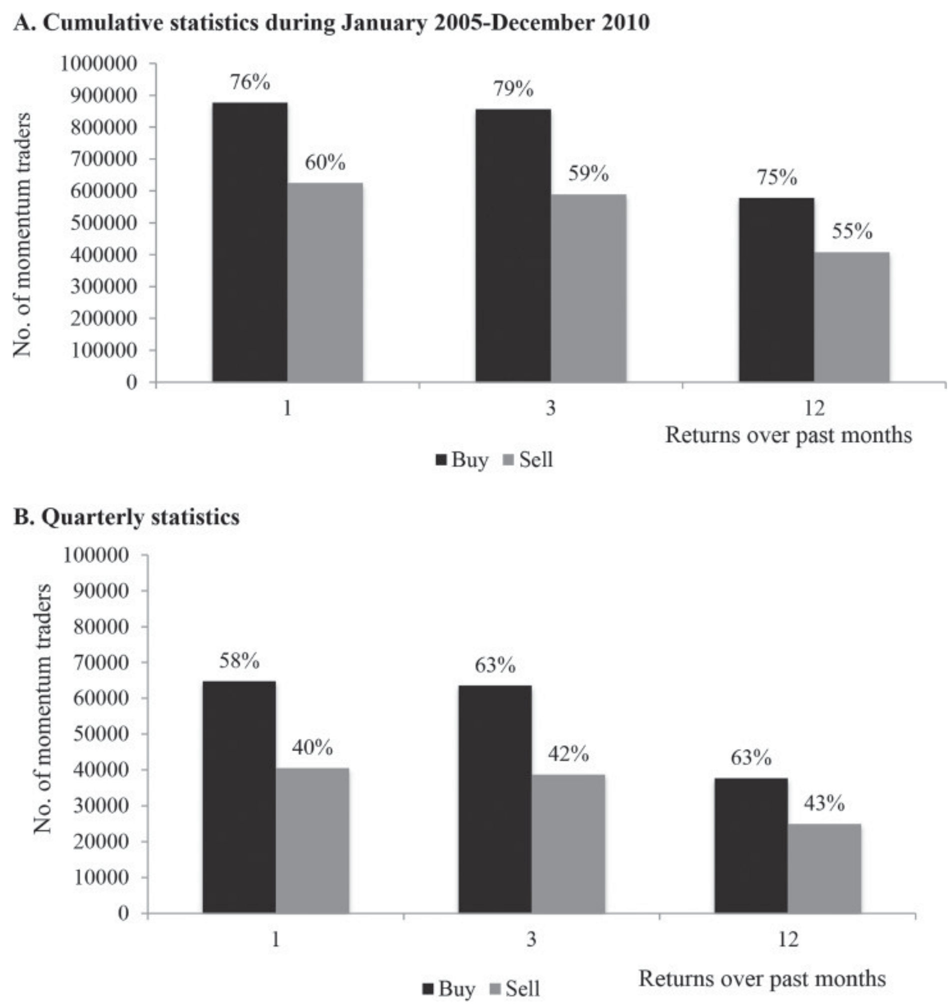

Fig. 1. Momentum traders statistics. (A) Cumulative statistics during January 2005 through December 2010, (B) quarterly statistics. *Note:* Panel A in this figure shows the cumulative number and percentage of buyers and sellers who followed momentum strategies in response to returns over past 1, 3, and 12 months during the sample period (January 2005 through December 2010). Percentage of momentum buyers (sellers) is calculated by dividing the total number of momentum buyers (sellers) by the total number of buyers (sellers) throughout the sample period. Panel B in this figure reports the quarterly momentum trading strategy. Number of momentum buyers (sellers) and total number of buyers (sellers) in each quarter are first calculated; then the average number and percentage of momentum buyers and sellers are shown in Panel B.

4. Performance of momentum traders

4.1. Performance measures

In this section, we ask whether momentum traders, as identified in the previous section, improve their portfolio performance. To address this point, we follow Zheng (1999) to evaluate trading performances.

We first construct three portfolios based on the quarterly momentum identifiers (876,941 momentum buyers and 624,307 momentum sellers) in response to past month fund return obtained in the previous section:

1. *Momentum buyer portfolio*: Long funds bought by a momentum buyer each month and weighted by fund's trading amount.
2. *Momentum seller portfolio*: Long funds sold by a momentum seller each month and weighted by fund's trading amount.
3. *Long-short portfolio*: Long the momentum buyer portfolio and short the momentum seller portfolio.

Portfolio 1 and 2 track what a trader purchases or sells each month in the quarter when he is identified as a momentum trader. For example, in the first quarter of 2008, if an individual is identified as a momentum buyer in response to past month return, a *momentum buyer portfolio* is constructed based on what he purchased each month in that quarter. However, if the individual stopped following momentum trading in the next quarter, his portfolio will not continue to be included in the momentum buyer portfolio next quarter. Portfolio 3 takes a long position in portfolio 1 and a short position in portfolio 2. That is, portfolio 3 evaluates the overall performance of momentum traders by buying what momentum buyers purchased and selling what momentum sellers sold. We also assume that investors hold the portfolio for six months in the baseline analysis. Therefore, once the portfolio is constructed, we calculate the average monthly return for the six months after the formation of portfolios.

We follow Zheng (1999) in using both excess returns and risk-adjusted returns to measure portfolio performance. The excess return is calculated as

$$R^e_{p,t} = R_{p,t} - R_{m,t} \tag{1}$$

where $R^e_{p,t}$ is the excess return of portfolio p in month t; $R_{p,t}$ indicates the value-weighted portfolio's monthly raw return; and $R_{m,t}$ is the market return in month t. Note that more than one trader can follow the same strategy each month. Thus, each month we calculate the cross-sectional average of portfolio excess returns realized by all traders following the same strategy. The time-series mean is presented and t-statistics indicate if the average return is statistically different from zero.

We use two methods to calculate risk-adjusted returns. The first is the "portfolio regression" approach, which estimates time-series regressions for returns of the portfolios. Both CAPM model and Fama-French three-factor model are used to adjust for risk. The second method is the "fund regression" approach, which estimates CAPM and Fama-French three-factor time-series regression for each fund and averages the α estimates across individual funds in the portfolio (Zheng, 1999).

In the first "portfolio regression" approach, we run the following OLS regressions:

$$\overline{R_{p,t}} - R_{f,t} = \alpha^1_p + \beta^1_p(R_{m,t} - R_{f,t}) + \varepsilon_{p,t} \tag{2}$$

$$\overline{R_{p,t}} - R_{f,t} = \alpha^3_p + \beta^3_{p,Rm}(R_{m,t} - R_{f,t}) + \beta^3_{p,SMB}SMB_t + \beta^3_{p,HML}HML_t + \varepsilon_{p,t} \tag{3}$$

where $\overline{R_{p,t}}$ is the cross-sectional average of raw returns realized by individual portfolios following the same strategy in month t; $R_{f,t}$ is the risk-free rate in month t; $R_{m,t}$ is the market return in month t; SMB_t is the return on the mimicking portfolio for the common size factor in stock returns in month t; and HML_t is the return on the mimicking portfolio for the common book-to-market equity factor in stock returns in month t. In each regression, α_p is the risk-adjusted excess return.

As Zheng (1999) points out, the "portfolio regression" approach does not require each fund to survive for a long period of time; however, it does not take into account time-varying portfolio compositions and risk characteristics. By contrast, the "fund regression" approach considers portfolio variation over time, but it requires each fund to have sufficient past return observations (30 monthly past returns in this study).[4] The α in the second approach are obtained by averaging the α estimates across individual funds in the portfolio:

$$R_{i,t} - R_{f,t} = \alpha_i^1 + \beta_i^1(R_{m,t} - R_{f,t}) + \varepsilon_{i,t} \quad (4)$$

$$R_{i,t} - R_{f,t} = \alpha_i^3 + \beta_{i,Rm}^3(R_{m,t} - R_{f,t}) + \beta_{i,SMB}^3 SMB_t + \beta_{i,HML}^3 HML_t + \varepsilon_{i,t} \quad (5)$$

$$\alpha_{p,t} = \sum(\alpha_i + \varepsilon_{i,t}) * \frac{\omega_{i,t}}{\sum \omega_{i,t}} \quad (6)$$

where $R_{i,t}$ indicates the rate of return of fund i in month t; $\alpha_{p,t}$ is the excess return of individual portfolio in month t; α_i and $\varepsilon_{i,t}$, which are used to calculate $\alpha_{p,t}$, are from Eqs. (4) and (5); and $\omega_{i,t}$ is the portfolio weight of fund i in month t. After obtaining $\alpha_{p,t}$ of each individual portfolio, we take the average across all traders following the same strategy in each month and show the time-series means and t-statistics on these averages.

4.2. Results

Table 2 Panel A shows performance of the three portfolios. Column (a) shows monthly excess return over market return as calculated by Eq. (1). Alphas in Columns (b) and (c) are risk-adjusted returns under the "portfolio regression" approach estimated by Eqs. (2) and (3). Alphas in Columns (d) and (e) report risk-adjusted returns under the "fund regression" approach estimated by Eqs. (4) through (6), which consider time-varying risk characteristics and portfolio compositions. Alpha1 in Columns (b) and (d) are risk-adjusted returns estimated by CAPM model, and alpha3 in Columns (c) and (e) are risk-adjusted returns estimated by the Fama-French three-factor model.

Results on momentum buyer portfolio (Portfolio 1) are mixed and none of the results is significantly different from zero. On the other hand, the significantly positive excess and risk-adjusted returns achieved by momentum seller portfolio (Portfolio 2) indicate that momentum sellers are following a losing strategy. They sell funds that significantly outperform the market in the following six months. For example, as estimated by Fama-French model under fund regression approach, momentum sellers lose 0.18% per month, which is equivalent to 2.14% per year. Overall, performance of Portfolio 3 shows that it is a losing strategy to buy what momentum buyers purchased and sell what momentum sellers sold in certain cases. The loss can be as high as 0.17% each month, which is equivalent to a 2.02% annual loss, when measured by CAPM model under fund regression approach.

Table 2 Performances of momentum traders (value-weighted)

Portfolios	(a) Excess return	(b) Alpha1-portfolio regression approach	(c) Alpha3-portfolio regression approach	(d) Alpha1-fund regression approach	(e) Alpha3-fund regression approach
A. Six-month holding period					
1. Momentum buyer	0.02%	0.01%	0.07%	−0.02%	0.05%
	(0.22)	(0.20)	(1.14)	(−0.27)	(0.62)
2. Momentum seller	0.13%**	0.13%**	0.11%**	0.15%**	0.18%***
	(2.62)	(2.60)	(2.00)	(2.59)	(3.38)
3. Portfolio 1 - Portfolio 2	−0.11%	−0.11%	−0.04%	−0.17%**	−0.13%**
	(−1.39)	(−1.40)	(−0.53)	(−2.13)	(−2.08)
B. One-month holding period					
1. Momentum buyer	0.06%	0.07%	0.08%	−0.03%	0.03%
	(0.35)	(0.41)	(0.44)	(−0.16)	(0.23)
2. Momentum seller	0.01%	0.003%	0.02%	0.08%	0.12%
	(0.05)	(0.02)	(0.13)	(0.52)	(0.81)
3. Portfolio 1 - Portfolio 2	0.05%	0.07%	0.06%	−0.11%	−0.09%
	(0.24)	(0.30)	(0.25)	(−0.56)	(−0.56)
C. One-year holding period					
1. Momentum buyer	0.03%	0.03%	0.07%	0.02%	0.04%
	(0.71)	(0.78)	(1.92)	(0.33)	(1.00)
2. Momentum seller	0.14%***	0.14%***	0.17%***	0.16%***	0.17%***
	(2.95)	(2.93)	(3.25)	(3.14)	(3.27)
3. Portfolio 1 - Portfolio 2	−0.11%	−0.11%	−0.10%	−0.14%**	−0.13%***
	(−1.85)	(−1.84)	(−1.72)	(−2.53)	(−2.75)
D. Financial turmoil period excluded, six-month holding period					
1. Momentum buyer	0.04%	0.05%	0.09%	−0.01%	0.003%
	(0.48)	(0.71)	(1.43)	(−0.13)	(0.04)
2. Momentum seller	0.10%	0.10%	0.10%	0.10%	0.14%**
	(1.95)	(1.93)	(1.72)	(1.70)	(2.55)
3. Portfolio 1 - Portfolio 2	−0.06%	−0.05%	−0.01%	−0.11%	−0.14%**
	(−0.76)	(−0.67)	(−0.17)	(−1.39)	(−2.01)
E. Consistent momentum traders (six-month holding period)					
1. Momentum buyer	0.03%	0.03%	0.08%	−0.01%	0.06%
	(0.33)	(0.35)	(1.17)	(−0.06)	(0.72)
2. Momentum seller	0.10%	0.11%	0.09%	0.12%	0.15%***
	(1.93)	(1.91)	(1.50)	(1.98)	(2.71)
3. Portfolio 1 - Portfolio 2	−0.08%	−0.08%	−0.01%	−0.12%	−0.09%
	(−0.86)	(−0.86)	(−0.13)	(−1.44)	(−1.36)

Note: Three portfolios are constructed based on 876,941 momentum buyers and 624,307 momentum sellers identified in response to past month fund return: (1) momentum buyer portfolio: purchase funds bought by a momentum buyer in the quarter he is identified as a momentum buyer, weighted by funds' trading amount; (2) momentum seller portfolio: purchase funds sold by a momentum seller in the quarter he is identified as a momentum seller, weighted by funds' trading amount; (3) portfolio 1- portfolio 2: long momentum buyer portfolio and short momentum seller portfolio. Excess return is calculated as the different between portfolio raw return and market return; cross-sectional average of excess returns among all momentum buyers (sellers) are first calculated each month and time-series mean and *t*-statistics are shown in Column (a); to calculate alpha1 and alpha3 under portfolio regression approach, we first obtain time-series raw returns by averaging portfolio raw returns across all momentum buyers (sellers) each month and risk-adjusted returns from CAPM and Fama-French three-factor models are shown in Column (b) and (c), respectively; Column (d) and (e) show the risk-adjusted returns under fund regression approach; alphas for individual momentum buyers (sellers) portfolios are first calculated using CAPM and Fama-French three-factor models and we take the average of alphas across all momentum buyers (sellers) each month and show the time-series means and *t*-statistics. Panel A includes the whole sample period (January 2005 through December 2010) and assumes holding period to be six months; Panel B and C assume holding periods are one month and one year, respectively; Panel D excludes the financial turmoil period (October 2008 through March 2010) from the whole sample period and shows average six-month performance; Panel E includes only consistent momentum traders (111,082 momentum buyers and 42,574 momentum sellers) and assumes holding periods to be six months. *t*-statistics are reported in parenthesis.

*** and ** indicate statistical significance at the 1% and 5% levels, respectively.

4.3. Performance with various holding periods

Thus far, we have assumed that traders hold the portfolio for six months. However, they may hold the portfolio for different periods. Accordingly, we next explore whether portfolio performance changes with various holding periods.

Table 2 Panel B shows the monthly excess returns and risk-adjusted returns for a holding period of one month, and Panel C shows the results for a one-year holding period. We find that even as the holding period changes, portfolio performance does not improve significantly. None of the portfolio performances is statistically significant when holding period is one month in Panel B. With a holding period of one year, momentum sellers lose significantly under all estimation models. The loss can be as high as 0.17% or 2.02% per year. The overall performance of momentum traders still yields significantly negative returns in certain cases. For example, monthly return of Portfolio 3 is 0.14%, or 1.67% annually under CAPM model (fund regression approach).

4.4. Effect of the financial crisis

Since the sample period includes the 2008–2009 financial crisis, it is necessary to test whether the performance results discussed above change when we exclude the turmoil period. We define the period of financial turmoil to be from October 2008 to March 2009. After excluding this period, we repeat the above analysis assuming holding periods being six months. The results, shown in Table 2 Panel D, are consistent with those reported earlier. Momentum traders do not benefit from momentum trading; they may even lose significantly with certain specifications. For example, as measured by Fama-French model under fund regression approach, momentum sellers lose 0.14% every month by selling the outperformed funds; overall, momentum traders lose 0.14% each month, which is equivalent to an annual loss of 1.67%.

4.5. Equally weighted portfolio

The performance of a portfolio is determined by two decisions: what funds are selected and how much is allocated to each selected fund. The above results based on value-weighted portfolios reflect the outcomes of both decisions. Is it possible that momentum traders in 401(k) plans still have the ability to select the right funds, but just fail to allocate the money wisely among these funds? To answer this question, we examine the performance of equally weighted portfolios.

The three portfolios under analysis are the same as in Table 2, except that they are constructed equally weighted. For example, when a trader was identified as a momentum buyer in the first quarter of 2009, we track what he purchased each month in that quarter and equally allocate money to these purchased funds to construct a momentum buyer portfolio (Portfolio 1). Then we calculate the average monthly return for various holding periods after portfolio was established.

Table 3 shows the performance of equally weighted portfolios. The results are consistent with previous findings. Momentum buyer portfolio (Portfolio 1) may be able to outperform

Table 3 Performances of momentum traders (equally-weighted)

Portfolios	(a) Excess return	(b) Alpha1-portfolio regression approach	(c) Alpha3-portfolio regression approach	(d) Alpha1-fund regression approach	(e) Alpha3-fund regression approach
A. Six-month holding period					
1. Momentum buyer	0.02%	0.02%	0.07%	−0.01%	0.05%
	(0.30)	(0.28)	(1.23)	(−0.19)	(0.67)
2. Momentum seller	0.13%***	0.13%***	0.12%**	0.15%**	0.18%***
	(2.77)	(2.75)	(2.15)	(2.64)	(3.38)
3. Portfolio 1 - Portfolio 2	−0.11%	−0.11%	−0.04%	−0.16%**	−0.13%**
	(−1.41)	(−1.41)	(−0.55)	(−2.10)	(−2.07)
B. One-month holding period					
1. Momentum buyer	0.06%	0.08%	0.09%	−0.01%	0.04%
	(0.39)	(0.44)	(0.47)	(−0.09)	(0.28)
2. Momentum seller	−0.02%	−0.03%	−0.01%	0.05%	0.09%
	(−0.13)	(−0.15)	(−0.03)	(0.34)	(0.59)
3. Portfolio 1 - Portfolio 2	0.09%	0.10%	0.09%	−0.07%	−0.05%
	(0.40)	(0.46)	(0.39)	(−0.36)	(−0.32)
C. One-year holding period					
1. Momentum buyer	0.03%	0.04%	0.07%**	0.02%	0.04%
	(0.79)	(0.85)	(2.03)	(0.05)	(0.14)
2. Momentum seller	0.15%***	0.15%***	0.17%***	0.16%***	0.18%***
	(3.07)	(3.05)	(3.33)	(3.19)	(3.32)
3. Portfolio 1 - Portfolio 2	−0.11%	−0.11%	−0.10%	−0.14%**	−0.13%***
	(−1.88)	(−1.88)	(−1.72)	(−2.51)	(−2.75)
D. Financial turmoil period excluded, six-month holding period					
1. Momentum buyer	0.04%	0.05%	0.09%	−0.01%	0.01%
	(0.54)	(0.77)	(1.50)	(−0.09)	(0.07)
2. Momentum seller	0.11%**	0.11%**	0.10%	0.10%	0.14%**
	(2.07)	(2.06)	(1.83)	(1.72)	(2.55)
3. Portfolio 1 - Portfolio 2	−0.07%	−0.05%	−0.01%	−0.11%	−0.13%**
	(−0.77)	(−0.69)	(−0.19)	(−1.36)	(−1.99)
E. Consistent momentum traders (six-month holding period)					
1. Momentum buyer	0.03%	0.03%	0.08%	−0.001%	0.06%
	(0.39)	(0.40)	(1.23)	(−0.01)	(0.73)
2. Momentum seller	0.11%**	0.11%	0.09%	0.12%**	0.15%***
	(2.00)	(1.99)	(1.55)	(2.05)	(2.69)
3. Portfolio 1 - Portfolio 2	−0.08%	−0.08%	−0.01%	−0.12%	−0.09%
	(−0.87)	(−0.87)	(−0.14)	(−1.45)	(−1.36)

Note: Three portfolios are constructed based on 876,941 momentum buyers and 624,307 momentum sellers identified in response to past month fund return: (1) momentum buyer portfolio: purchase funds bought by a momentum buyer in the quarter he is identified as a momentum buyer, each fund is equally-weighted; (2) momentum seller portfolio: purchase funds sold by a momentum seller in the quarter he is identified as a momentum seller, each fund is equally weighted; (3) portfolio 1- Portfolio 2: long momentum buyer portfolio and short momentum seller portfolio. Excess return is calculated as the different between portfolio raw return and market return; cross-sectional average of excess returns among all momentum buyers (sellers) are first calculated each month and time-series mean and *t*-statistics are shown in Column (a); to calculate alpha1 and alpha3 under portfolio regression approach, we first obtain time-series raw returns by averaging portfolio raw returns across all momentum buyers (sellers) each month and risk-adjusted returns from CAPM and Fama-French three-factor models are shown in Column (b) and (c), respectively; Column (d) and (e) show the risk-adjusted returns under fund regression approach; alphas for individual momentum buyers (sellers) portfolios are first calculated using CAPM and Fama-French three-factor models and we take the average of alphas across all momentum buyers (sellers) each month and show the time-series means and *t*-statistics. Panel A includes the whole sample period (January 2005 through December 2010) and assumes holding period to be six months; Panel B and C assume holding periods are one month and one year, respectively; Panel D excludes the financial turmoil period (October 2008 through March 2010) from the whole sample period and shows average six-month performance; Panel E includes only consistent momentum traders (111,082 momentum buyers and 42,574 momentum sellers) and assumes holding periods to be six months. *t*-statistics are reported in parenthesis.

*** and ** indicate statistical significance at the 1% and 5% levels, respectively.

the market in certain cases. However, momentum sellers lose significantly by selling good performers. Overall, Portfolio 3 has significantly negative risk-adjusted returns with certain specifications. These findings suggest that momentum traders do not display the ability to select the right funds to outperform the market.

4.6. Consistent momentum traders

The binomial test we used identifies momentum traders quarterly. It is possible for an investor to follow momentum trading strategy in a quarter and abandon the strategy later. The above analysis showed that momentum traders lose significantly. Is it possible for a subgroup of momentum traders who consistently follow momentum trading strategies to perform better? If an investor consistently adopts the same strategy whenever he trades, he is expected to take this strategy more seriously and have a higher chance to benefit from it than other strategy followers.

In this subsection, we select a subsample of momentum traders who consistently followed the momentum trading strategy during the sample period. A consistent momentum buyer is a trader who followed momentum buy strategy whenever he made a purchase in any quarter during sample period. The same criterion is used to identify consistent momentum sellers. We excluded those who purchased or sold only in one quarter during the sample period. We obtained 111,082 consistent momentum buyers, who represent 9.7% of buyers or 12.7% of momentum buyers during the sample period; there were 42,574 consistent momentum sellers representing 4.1% of all sellers or 6.8% of momentum sellers. We study consistent momentum traders' portfolio performance as we did in previous sections. As shown in Panel E in Table 2 and 3, performance of these consistent or most momentum oriented momentum traders is similar to other momentum traders. They do not benefit from momentum trading; instead they sell outperformed funds.

4.7. Identify momentum traders with different returns

In this subsection, we test if results will change when we use different criteria to define momentum traders. In our baseline analysis, we identified momentum traders based on their reactions to past month return and found their wealth suffers from momentum trading. Now we identify momentum traders in each quarter based on their responses to returns over the past quarter ($j = 3$) and year ($j = 12$). For example, to identify momentum traders in a quarter based on return over the past 3 months, we calculate the number of funds with positive and negative returns in the previous quarter and rerun the binomial tests described in Section 3. We identified 856,358 (589,243) momentum buyers (sellers) in response to returns over the past 3 months and 577,626 (408,253) momentum buyers (sellers) in response to fund returns over the past 12 months. Results in Table 4 based on newly identified momentum traders' portfolios are consistent with previous findings. For example, momentum sellers identified by using returns over past quarter lose 0.16% each month by selling outperformed funds, as estimated by CAPM model under portfolio regression approach. Overall, momentum traders lose 0.18% each month, or 2.14% annually in Portfolio 3.

Table 4 Performances of momentum traders based on *j*-month lagged returns

Portfolios	(a) Excess return	(b) Alpha1-portfolio regression approach	(c) Alpha3-portfolio regression approach	(d) Alpha1-fund regression approach	(e) Alpha3-fund regression approach
A. Momentum trading (j = 3)					
1. Momentum buyer	−0.02%	−0.02%	0.04%	0.06%	0.03%
	(−0.22)	(−0.23)	(0.65)	(0.78)	(0.43)
2. Momentum seller	0.17%***	0.16%***	0.14%***	0.14%**	0.17%***
	(3.20)	(3.18)	(2.77)	(2.35)	(2.94)
3. Portfolio 1 - Portfolio 2	−0.18%**	−0.18%**	−0.10%	−0.09%	−0.14%**
	(−2.40)	(−2.39)	(−1.57)	(−1.25)	(−2.04)
B. Momentum trading (j = 12)					
1. Momentum buyer	0.06%	0.02%	0.09%	−0.05%	−0.07%
	(0.62)	(0.34)	(1.35)	(−0.56)	(−0.80)
2. Momentum seller	0.19%**	0.20%**	0.23%***	0.08%	0.11%
	(2.16)	(2.12)	(2.78)	(0.93)	(1.57)
3. Portfolio 1 - Portfolio 2	−0.13%	−0.17%	−0.15%	−0.13%	−0.18%**
	(−1.24)	(−1.84)	(−1.37)	(−1.32)	(−2.34)

Note: Three portfolios are constructed based on 856,358 (589,243) momentum buyers (sellers) identified in response to fund returns over the past three months in Panel A, and 577,626 (408,253) momentum buyers (sellers) identified in response to fund returns over the past 12 months in Panel C. Three constructed portfolios are: (1) momentum buyer portfolio: purchase funds bought by a momentum buyer in the quarter he is identified as a momentum buyer, weighted by funds' trading amount; (2) momentum seller portfolio: purchase funds sold by a momentum seller in the quarter he is identified as a momentum seller, weighted by funds' trading amount; (3) portfolio 1- portfolio 2: long momentum buyer portfolio and short momentum seller portfolio. Holding period is six months. Excess return is calculated as the different between portfolio raw return and market return; cross-sectional average of excess returns among all momentum buyers (sellers) are first calculated each month and time-series mean and *t*-statistics are shown in Column (a); to calculate alpha1 and alpha3 under portfolio regression approach, we first obtain time-series raw returns by averaging portfolio raw returns across all momentum buyers (sellers) each month and risk-adjusted returns from CAPM and Fama-French three-factor models are shown in Column (b) and (c), respectively; Column (d) and (e) show the risk-adjusted returns under fund regression approach; alphas for individual momentum buyers (sellers) portfolios are first calculated using CAPM and Fama-French three-factor models and we take the average of alphas across all momentum buyers (sellers) each month and show the time-series means and *t*-statistics. *t*-statistics are reported in parenthesis.

*** and ** indicate statistical significance at the 1% and 5% levels, respectively.

4.8. Investment opportunity constraints

Last, we explore the possibility that 401(k) momentum traders lose because of investment opportunity constraints in plan offerings, instead of their lack of selection ability. It is known that 401(k) participants are offered a limited set of funds to invest in each plan. Their investment opportunity might be constrained if the funds offered are underperformed ones, which could cause investment loss (Tang et al., 2010).

To exclude such possibility, we construct an average fund portfolio, which invests in all available equity assets in the plan. It measures the performance the average investors realize in the 401(k) accounts. The value-weighted average fund portfolio has an excess return of 0.06% assuming holding period of six months; alphas from CAPM and Fama-French models are 0.06% and 0.07%, respectively, under portfolio regression approach; alphas from CAPM and Fama-French models are both 0.07% under fund regression approach. Comparing with results in Panel A Table 2, these statistics indicate that the average equity fund in the sample 401(k) plans outperformed the market during the testing period; however, momentum traders buy funds underperforming the average fund and sell funds outperforming the average fund, which leads to a significant loss by momentum traders. Their loss is because of their lack of selection ability instead of investment opportunity constraints. We obtained the same conclusion with other holding periods and with equally weighted average fund portfolio.

Hence, we conclude that momentum traders in 401(k) plans lose significantly. Although they move towards good performers in certain cases, they move away from good performers as well. Even though 401(k) traders trade infrequently and pay limited transaction costs, they do not benefit from momentum trading. If performance improvement is not linked to feedback trading, then what are the causes of such inefficiency?

5. Explaining 401(k) momentum trader inefficiency

Given the meaningful inefficiencies identified among 401(k) momentum traders, the next step is to locate the causes of the inefficiency. At the participant level, it could be because of traders' lack of fund selection ability. Previous studies have indicated that the stock return momentum phenomenon documented by Jegadeesh and Titman (1993) explains the mutual fund performance persistence (Carhart, 1997; Grinblatt et al., 1995). Specifically, because stock returns are positively correlated in the short term, funds that consistently invest in recent winner stocks would benefit more than other funds from the effects of return momentum of underlying stocks (Sapp and Tiwari, 2004). Such momentum investing style is the key to persistent mutual fund outperformance. Consequently, if investors want to realize excess return by chasing past fund performance, it is important to select funds that take advantage of a momentum investing style. Chasing recent winners might unwittingly benefits from the momentum effect if the purchased winning funds happen to invest on momentum; however, a strategy of naively chasing past performance while lacking the ability to identify funds with momentum styles cannot guarantee the success of momentum trading (Sapp and Tiwari, 2004). Sapp and Tiwari (2004) have indicated that investors of U.S. mutual funds lack fund selection ability; they do not select funds based on a momentum investing style, but rather simply chase funds that were recent winners. If the same pattern holds true among 401(k) traders, this could be one explanation for the inefficiency among 401(k) momentum traders. In this section, we will test whether momentum traders in 401(k) plans have the ability to identify funds with momentum styles or whether they just naively chase past fund performance.

5.1. Determinants of fund cash flows

If investors have the ability to identify funds with momentum styles, we would expect fund momentum loadings to significantly affect fund cash flows. However, if investors simply chase past fund performance, we would expect lagged fund returns to be the primary determinant of fund cash flows. We follow Sapp and Tiwari (2004) to examine the explanatory power of momentum factor loading and lagged fund return for fund cash flows.

To do so, we first estimate individual funds' momentum factor loadings each month by the following four-factor model:

Table 5 Determinants of fund cash flows

Explanatory variables	Momentum buyer		Momentum seller	
	I	II	I	II
Intercept	0.10***	−0.47	−0.14***	−0.08***
	(6.25)	(−1.36)	(−17.60)	(−8.43)
Past month fund return	0.50	0.88	0.06***	0.11***
	(1.80)	(1.83)	(3.08)	(5.92)
UMD loading	0.01	0.002	0.001	0.0003
	(0.55)	(0.23)	(0.18)	(0.12)
Logarithm of fund size		0.03		−0.003***
		(1.71)		(−8.30)
Previous month's fund cash flow		−0.0005		0.08***
		(−0.53)		(8.03)

Note: The table shows the coefficients from regressions of the determinants of momentum buyers' and momentum sellers' normalized fund cash flows. Dependents variables are average monthly cash flows of funds purchased (sold) by momentum buyers (sellers) normalized by individual traders' account balance at the beginning of the month. Independent variables include past month fund return, fund's UMD loading estimated from four-factor model, logarithm of the funds total assets at the beginning of the month, and normalized fund cash flow in the previous month. Regressions also control for time fixed effects. *t*-statistics are reported in parenthesis.

*** and ** indicate statistical significance at the 1% and 5% levels, respectively.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{i,t} \tag{7}$$

where $R_{i,t}$ is the monthly return of fund i; $R_{f,t}$ is the monthly risk-free asset return; $R_{m,t}$ is the market return in month t. SMB, HML, and UMD are returns on zero-investment factor-mimicking portfolios for size, book-to-market, and one-year momentum in stock returns. Therefore, β_4 indicates the estimated momentum factor loading of fund i.

We then run the regression to investigate the determinants of fund cash flows. Specifically, in the quarter when a trader is identified as a momentum trader, we normalize the monthly cash flows of each fund purchased (sold) by the momentum buyer (seller) by his account balance at the beginning of the month. We then take the monthly average of normalized cash flows of each fund across all traders and use the averages as dependent variables. Independent variables in the regression include fund's UMD loading and funds' past month returns. We choose past month return because momentum traders are identified based on their responses to past month fund return. Regressions also control for time fixed effects.

Model I in Table 5 uses a fund's lagged return and UMD loading as explanatory variables. Results show that UMD loading has no significant impact on momentum traders' cash flows. At the same time, past fund returns are significantly positively related to cash flows ($p<.10$ among momentum buyers; $p<.01$ among momentum sellers). Model II includes additional explanatory variables in the regression, namely logarithm of funds total assets at the beginning of the month, and normalized fund cash flows in the prior month. Larger funds presumably have greater visibility and thus are expected to have larger transaction amounts involved. Results confirm that larger funds have more cash outflows. The positive coefficient on previous month's fund cash flow among momentum sellers suggests that cash outflow tends to be persistent, probably because of fund reputation or visibility. Results from Model

Table 6 Percentage of funds traded by momentum traders based on momentum factor rankings (in %)

Momentum factor loading ranks	Momentum buyer		Momentum seller	
	Mean	SD	Mean	SD
0~1st quartile	22.03	30.03	26.42	31.64
1st-2nd quartile	25.29	32.99	23.64	31.55
2nd-3rd quartile	20.67	30.35	19.40	29.20
3rd-4th quartile	32.01	33.87	30.54	32.84

Note: Momentum factor loading for each fund is estimated by the four-factor model. Funds are then ranked within a plan into quartiles based on funds' momentum factor loadings. The table reports for each momentum factor loading quartile, the percentage of funds purchased by momentum buyers and sold by momentum seller.

II also confirm that cash flows of momentum traders are primarily influenced by past returns rather than by fund momentum exposures (coefficient on past month fund return among momentum buyers in model II is significant at $p<.10$). In summary, evidence from Table 5 suggests that momentum traders in 401(k) plans lack the ability to identify funds with momentum styles. They just naively chase past fund performance.

5.2. Relationship between fund cash flows and fund momentum exposures

The above findings confirm that past fund returns, instead of fund momentum exposures, are primary determinants of momentum traders' cash flows. To further explore this issue, we follow Sapp and Tiwari (2004) and examine whether 401(k) momentum traders persistently trade funds with high momentum exposures.

We rank the funds within a plan into quartiles based on funds' momentum factor loadings as calculated above. We then calculate for each momentum quartile the proportion of funds purchased by momentum buyers and sold by momentum sellers in the quarter they are identified as momentum traders.

As shown in Table 6, momentum traders do not appear to deliberately pursue a strategy of investing in momentum-style funds. For example, only 32.01% of the funds purchased by the momentum buyers are the "momentum funds" that have the highest momentum exposures, whereas 22.03% of the funds they purchase belong to the lowest momentum factor quartile.

The above results indicate that momentum traders in 401(k) plans naïvely chase funds according to funds' past returns rather than successfully identifying funds that follow a momentum style. These traders do not follow a deliberate strategy of selectively investing in momentum funds. Such a naïve momentum strategy hinders the profitability of momentum investing.

6. Discussions

Empirical results on investor trading performance are mixed in the literature. There is evidence indicating "smart money" effects among investors. Gruber (1996) and Zheng

(1999) show that the short-term performance of funds that experience positive cash flow is significantly better than those experiencing negative cash flow, suggesting that mutual fund investors have selection ability and invest accordingly. Subsequent work by Sapp and Tiwari (2004) confirms the smart money effect using the complete universe of U.S. equity mutual funds for the period 1970 through 2000, and it further shows that stock return momentum phenomenon explains the smart money effect. On the other hand, other studies indicate the existence of "dumb money" effects. For example, Frazzini and Lamont (2008) find that retail investors direct their money to funds that invest in stocks with high past returns (momentum trading). However, by overweighting growth stocks and selecting securities that on average underperform their growth benchmarks, investors end up with stocks having low future returns. Mutual fund investors are "dumb" in the sense that they lose money from their reallocations. They fail to utilize momentum in a systematic way as documented in Jegadeesh and Tittman (1993).

Before we draw the conclusion that our results contradict the "smart money" effects, we would like to check if we could replicate the smart money effects using Zheng (1999) methodology. In particular, Zheng (1999) aggregates trading data across individuals. The rich dataset we adopted allows us to study trading behaviors at the individual investor level. As robustness check, we now aggregate fund flows of momentum buyers and sellers. We follow Zheng (1999) to construct portfolios at the beginning of each quarter based on the sign of new money in the preceding quarter.

Portfolio 1: In all funds with positive new money cash flows by momentum buyers and weighted by funds' new money.

Portfolio 2: In all funds with negative new money cash flows by momentum sellers and weighted by funds' new money.

These portfolios correspond to portfolios 5 to 6 in Zheng (1999). We then follow the portfolios for three months and calculate their monthly returns as Zheng (1999) did. As shown in Table 7, there is no sign of smart money effects even after we aggregated the cash flows of momentum buyers and sellers. Thus, our results are in line with the literature on the "dumb money" effects.

We consider several factors that could contribute to the contrast between our findings and prior literature on "smart money" effects. First, portfolios under analysis here differ from prior studies. This article investigates the performance of momentum traders exclusively; whereas Gruber (1996) and Zheng (1999) focus on trading strategies by all types of traders. The "dumb money" effects among momentum traders found in this article do not exclude the possibility that investors could make "smart money" through other trading strategies. Second, we study a different group of investors. As pointed out in the introduction, investors may exhibit different behavior when trading in and outside retirement accounts. Given that 401(k) plan participants may have less resource necessary to implement a mechanical funds selection rule, and they may pay less attention to their account performance because of inertial and other behavioral biases than active traders outside retirement accounts, it is reasonable to expect different performance outcomes (see, e.g., Agnew et al., 2003; Ameriks and Zeldes, 2004). Third, our sample period covers 2005 through 2010. Although we have examined the impact of financial crisis and investment opportunity constraints on momentum

Table 7 Performance of new money portfolios (aggregated fund cash flows)

Portfolios	(a) Excess return	(b) Alpha1-portfolio regression approach	(c) Alpha3-portfolio regression approach	(d) Alpha1-fund regression approach	(e) Alpha 3-fund regression approach
1. Positive cash flow	−0.003%	−0.01%	−0.01%	−0.002%	0.02%
	(−0.03)	(−0.06)	(−0.06)	(−0.02)	(0.19)
2. Negative cash flow	0.12%	0.12%	0.11%	0.18%	0.17%
	(1.13)	(1.09)	(1.09)	(1.56)	(1.60)
Portfolio 1 - Portfolio 1	−0.12%	−0.13%	−0.12%	−0.18%**	−0.15%**
	(−1.40)	(−1.38)	(−1.33)	(−2.21)	(−2.28)

Note: Three portfolios are constructed based on 876,941 momentum buyers and 624,307 momentum sellers identified in response to past month fund return: (1) positive cash flow portfolio: purchase all funds with positive new money cash flows by momentum buyers in the quarter they are identified as momentum buyers, weighted by funds' new money; (2) negative cash flow portfolio: purchase all funds with negative new money cash flows by momentum sellers in the quarter they are identified as momentum sellers, weighted by funds' new money; (3) portfolio 1- portfolio 2: long positive cash flow portfolio and short negative cash flow portfolio. The holding period for each portfolio is three months. Excess return is calculated as the different between portfolio raw return and market return; cross-sectional average of excess returns among all momentum buyers (sellers) are first calculated each month and time-series mean and *t*-statistics are shown in Column (a); to calculate alpha1 and alpha3 under portfolio regression approach, we first obtain time-series raw returns by averaging portfolio raw returns across all momentum buyers (sellers) each month and risk-adjusted returns from CAPM and Fama-French three-factor models are shown in Column (b) and (c) respectively; Column (d) and (e) show the risk-adjusted returns under fund regression approach; alphas for individual momentum buyers (sellers) portfolios are first calculated using CAPM and Fama-French three-factor models and we take the average of alphas across all momentum buyers (sellers) each month and show the time-series means and *t*-statistics. *t*-statistics are reported in parenthesis.

*** and ** indicate statistical significance at the 1% and 5% levels, respectively.

traders' performances, caution should be taken to imply the results to other years. We invite further study to examine momentum trading performance during other sample periods.

7. Conclusions

This article explores the existence and performance of momentum traders in 401(k) plans. Our unique dataset and our use of the binomial test make it possible to distinguish momentum traders from random traders in each quarter. Using various measures of risk-adjusted returns with different holding periods, we find that momentum traders in 401(k) plans do not improve their portfolio performance. Instead, they could lose up to 2.14% per year. We further confirmed our conclusions by excluding inconsistent momentum traders from the sample. In seeking to explain such inefficiency, we find that 401(k) traders follow a naïve momentum strategy. That is, they do not have the ability to select funds with momentum investing styles but, instead, simply chase past returns.

The substantial growth of 401(k) pensions in the American workplace in recent decades has generated much interest in how well these retirement schemes are managed and how plan sponsors can help participants better manage their retirement savings. Previous studies indicate that Americans are not adequately planning for their retirement futures (Willett, 2008). Academic researchers have indicated some behavioral biases and financial literacy constraints that hurt 401(k) investment efficiency. While previous studies have investigated 401(k) decisions on contribution and asset allocation, we locate another source of 401(k) management inefficiency—loss caused by momentum trading. Pension plan participants seem to lack sufficient trading knowledge and fund selection ability to benefit from momentum trading in 401(k) plans. They adopt momentum strategies irrationally. As a consequence, momentum traders lose from trading in 401(k) plans. In addition, inefficient momentum traders may exert negative impacts on long-term investors in the fund. The withdrawal of momentum traders after experiencing negative returns may force open-end funds to sell assets at depressed values to meet redemption requests, which could potentially cause losses to other investors in the fund.

One way to rectify errors produced by counterproductive trading would be to improve financial education and investment literacy levels (Dolvin and Templeton, 2006). In addition, helpful "nudges" by employers are suggested (Thaler and Sunstein, 2008). As pointed out by Thaler and Sunstein (2008), well-designed choice architecture could steer people's choices in directions that will improve their lives. Default options are considered helpful to combat irrational investment behaviors. For example, the 2006 Pension Protection Act authorized a series of "qualified default investment alternatives" (QDIAs). Target-date funds (TDFs), one of the alternatives, are funds diversified across stocks and bonds that automatically rebalance toward lower risk investments as participants approach retirement. We expect that such a design will help avoid losses caused by 401(k) participants' behavior biases in portfolio choices and trading. In addition, pension designers may want to mitigate the impact of counterproductive momentum trading by muting naïve momentum trading itself, perhaps by making short-term performance less salient to investors, especially to those who experience balance shocks or portfolio losses.

Notes

1 We count a buy or sell transaction on a daily basis as one trade. To calculate individual turnover, we follow Annew et al. (2003). We sum the absolute values of trading amount in one year and divide this sum by two. We then divide the annual trading amount by the account balance at the beginning of the year.
2 The majority of 401(k) investment assets under analysis are mutual funds.
3 The total number of buyers and sellers is more than the total number of traders during the sample period because a trader could both buy and sell. In that case, he will be considered as one observation in buyers sample, one observation in sellers sample, and one, instead of two, observation in traders sample.
4 If the fund has fewer than 30 past return observations in month t, traders who purchased or sold that fund in month t are excluded from the sample. Losing observations is the disadvantage of the "fund regression" approach compared with the "portfolio regression" approach.

References

Agnew, J. (2002). *Inefficient Choices in 401(k) Plans: Evidence From Individual Level Data*. Presented at the 4th Annual Joint Conference for the Retirement Research Consortium 'Directions for Social Security Reform.' May 2002, Washington, D.C.

Agnew, J., Balduzzi, P., & Sunden, A. (2003). Portfolio choice and trading in a large 401(k) plan. *American Economic Review*, *93*, 193–215.

Ameriks, J., & Zeldes, S. P. (2004). *How Do Household Portfolio Shares Vary With Age?* TIAA-CREF working paper.

Barber, B., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance*, *55*, 773–806.

Benartzi, S., Thaler, & R. H. (2001). Naïve diversification strategies in defined contribution savings plans. *American Economic Review*, *91*, 79–98.

Benartzi, S., Thaler, R. H., Utkus, S. P., & Sunstein, C. R. (2007). The law and economics of company stock in 401(k) plans. *Journal of Law and Economics, 50*, 45–79.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance, 52*, 57–82.

Choi, C. J., Laibson, D., & Madrian, B. D. (2007). *Mental Accounting in Portfolio Choice: Evidence From a Flypaper Effect.* NBER working paper 13656.

Dolvin, S., & Templeton, W. (2006). Financial education and asset allocation. *Financial Services Review*, *15*, 133–149.

Even, W. E., & Macpherson, D. A. (2008). Pension investments in employer stock. *Journal of Pension Economics and Finance*, *7*, 67–93.

Frazzini, A., & Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*, *88*, 299–322.

Goetzmann, W. N., & Ibbotson, R. G. (1994). Do winners repeat? *Journal of Portfolio Management*, *20*, 9–18.

Goetzmann, W., & Massa, M. (2002). Daily momentum and contrarian behavior of index fund investors. *Journal of Financial and Quantitative Analysis*, *37*, 375–389.

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: A study of Finland's unique data set. *Journal of Financial Economics. 55*, 43–67.

Grinblatt, M., & Keloharju M. (2001). What makes investors trade? *Journal of Finance*, *56*, 589–616.

Grinblatt, M., & Titman, S. (1992). The persistence of mutual fund performance. *Journal of Finance*, *47*, 1977–1984.

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review*, *85*, 1088–1105.

Gruber, M. (1996). Another puzzle: The growth in actively managed mutual funds. *Journal of Finance*, *51*, 783–810.

Hendricks, D., Patel, J., & Zechhauser, R. (1993). Hot hands in mutual funds: short-run persistence of relative performance, 1974–1988. *Journal of Finance*, *48*, 93–130.

Huberman, G., & Sengmueller, P. (2004). Performance and employer stock in 401(k) plans. *Review of Finance*, *8*, 403–443.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance*, *48*, 65–91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: an evaluation of alternative explanations. *Journal of Finance*, *56*, 699–720.

Kim, K. T., & Hanna, S. D. (2015). Do U.S. households perceive their retirement preparedness realistically? *Financial Services Review*, *24*, 139–155.

Liang, N., & Weisbenner, S. (2002). *Investor Behavior and the Purchase of Company Stock in 401(k) Plans: The Importance of Plan Design. Finance and Economics Discussion Series 2002–36.* Washington, DC: Board of Governors of the Federal Reserve System.

Pettengill, G. N., Edwards, S. M., & Schmitt, D. E. (2006). Is momentum investing a viable strategy for individual investors? *Financial Services Review*, *15*, 181–197.

Pettengill, G. N., Edwards, S. M., & Griggs, F. T. (2009). Can individual investors duplicate professional momentum investing? *Financial Services Review*, *18*, 355–380.

Rockenbach, B. (2004). The behavioral relevance of mental accounting for the pricing of financial options. *Journal of Economic Behavior & Organization*, *53*, 513–527.

Rouwenhorst, K. G. (1998). International momentum strategies. *Journal of Finance*, *53*, 267–284.

Sapp, T., & Tiwari, A. (2004). Does stock return momentum explain the "smart money" effect? *Journal of Finance*, *59*, 2605–2622.

Sirri, E., & Tufano, P. (1998). Costly search and mutual fund flows. *Journal of Finance*, *53*, 1589–1622.

Solomon, D. H., Solges, E., & Sosyura, D. (2014). Winners in the spotlight: Media coverage of fund holdings as a driver of flows. *Journal of Financial Economics*, *113*, 53–72.

Tang, N., Mitchell, O. S., & Utkus, S. P. (2012). Trading in 401(k) plans during the financial crisis. In: R. Maurer, O. S. Mitchell, & M. J. Warshawsky (Eds.), *Reshaping Retirement Security: Lessons from the Global Financial Crisis.* Oxford: Oxford University Press.

Tang, N., Mitchell, O. S., Mottola, G. R., & Utkus, S. P. (2010). The efficiency of sponsor and participant portfolio choices in 401(k) plans. *Journal of Public Economics*, *94*, 1973–1085.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving Decisions about Health, Wealth, and Happiness.* New Haven, CT: Yale University Press.

VanDerhei, J., Holden, S., Alonso, L., & Bass, S. (2011). *401(k) Plan Asset Allocation, Account Balances, and Loan Activity in 2010*. EBRI Issue Brief #366.

Warther, V. (1995). Aggregate mutual fund flows and security returns. *Journal of Financial Economics*, *39*, 581–562.

Willett, M. (2008). A new model for retirement education and counseling. *Financial Services Review*, *17*, 105–130.

Zheng, L. (1999). Is money smart? A study of mutual fund investors' fund selection ability. *Journal of Finance*, *54*, 901–933.