

Individual Investor Activity and Performance

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Abstract

We examine the activity and performance of a large panel of individual investors (approximately 70,000 investors and their daily returns over the 2000 to 2010 period) in Sweden's Premium Pension System. We document strong inertia in individuals' choices and changes of mutual funds. We find that active investors outperform passive investors, and that there is a causal effect of fund changes on performance. The outperformance is primarily the result of dynamic fund selection. Activity is beneficial for the individual investor, whereas extreme flows out of mutual funds (which we attribute to financial advisors) affect funds' net asset value negatively for all investors.

Keywords: Coordinated fund changes, financial advisors, fire sales, 401(k).

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1 Introduction

Pension and savings schemes where investment decisions are made by plan participants have grown steadily over the past three decades. These schemes have many attractive features, such as portability and flexibility, but place greater responsibility on individuals to make decisions and monitor their choices. Much to the concern of pension authorities, a wealth of evidence indicates that most plan participants are passive and fail to live up to these expectations (see, e.g., Madrian and Shea, 2001; Benartzi and Thaler, 2001; Choi, Laibson, Madrian and Metrick, 2002; Agnew, Balduzzi, and Sundén, 2003; and Mitchell, Mottola, Utkus, and Yamaguchi, 2006).

We study the activity and performance of pension investors in a modern defined contribution plan. We also investigate whether the activity of some investors affects other investors. We have detailed data on a population of more than six million individuals in the Swedish Premium Pension System for the period December 2000 to May 2010. We mainly consider a sample of approximately 70,000 individuals, and track their choices and changes of mutual funds on a daily basis.

We find that investors who are actively involved in managing their pension accounts earn significantly higher returns than passive investors. Individuals with an active initial selection and no subsequent changes earn returns of 1.7% per year, whereas individuals who make more changes earn returns of 2.5%-8.6% per year. The activity-performance relationship is monotonically increasing. Differences in risk-adjusted returns are similar, suggesting that higher returns are attributable to better investment performance rather than risk compensation.

We argue that activity leads to higher performance. Active investors may simply be better educated or better informed, but a closer look at the differences in performance suggests that changing funds is instrumental. When we construct counterfactual returns by discarding

fund changes, the differences in performance between active and passive investors are much smaller. Our results also indicate that individuals who are more active make marginally better initial fund choices. However, their better performance is primarily the result of their changing funds within an asset class (fund selection) and not across asset classes (market timing). This latter result is consistent with the results of Agnew, Balduzzi, and Sundén (2003), and Choi, Laibson, and Metrick (2002), who use predictive regressions to show that 401(k) investors lack market timing ability. Moreover, our evidence suggests that active investors manage to invest in well-performing funds by exploiting mutual fund momentum. Put differently, passive investors seem to remain invested in persistently poorly-performing funds.

The picture emerging from our analysis is that it is important for pension savers to manage and monitor their accounts. This is not a foregone conclusion. Indirect evidence from the mutual fund literature has traditionally been inconclusive regarding the link between activity and performance. The evidence in favor of “smart money” effects (see, e.g., Gruber, 1996; and Zheng, 1999) conflicts with studies pointing to “dumb money” effects (Frazzini and Lamont, 2008) and with evidence from studies of individuals trading in brokerage accounts (see, e.g., Barber and Odean, 2000 and 2002). However, as emphasized by Coval, Hirshleifer, and Shumway (2005), not all individuals do poorly in their investments.

Many of the individuals’ fund changes are coordinated, which we attribute to financial advisors who give recommendations and manage portfolios on a discretionary basis. We estimate that coordinated investors accounted for 10% of the population, but executed 80% of all fund changes in 2010. We find neutral performance for most coordinated investors, and only very active investors seem to achieve higher performance.

Our results reveal a dark side to high levels of investor activity, especially coordinated fund changes. A high level of activity may impose a negative externality on passive investors. Active investors force mutual fund managers to trade more, and this induced trading can

negatively impact fund returns. Since the costs are borne by the fund, shareholders who trade implicitly impose a financial burden on others in the fund. This problem is greatly aggravated by the presence of large financial advisors who exacerbate trading demands, and the coordination of these demands, threatening to generate significant transaction costs and wealth transfers. The sources of these costs vary. They may be due to brokerage and price impact costs from increased fund trading (Edelen, 1999), fire sales of assets following sudden fund redemptions (Coval and Stafford, 2007), administrative costs, and exclusion of illiquid investment options from pension menus.¹ These costs can be large when there are no load, exit or redemption fees to dampen investor trading. Our results suggest that the costs caused by active investors can be as high as 0.5% of a fund's assets under management for an extreme fund outflow. We argue that these costs are most likely driven and exacerbated by financial advisors.

The rest of the paper is organized as follows. Section 2 describes the Swedish Premium Pension System. The data and estimation methods are outlined in Sections 3 and 4. Section 5 presents the main results on the activity and performance of individual investors. Section 6 presents brief results for coordinated investors. Section 7 explores whether extreme outflows affect the mutual funds' net asset values and thereby also other investors. Section 8 concludes. The results of a Monte Carlo experiment are presented in the Appendix.

2 The Premium Pension System in Sweden

The public pension system in Sweden consists of two components: a notional defined contribution plan financed on a pay-as-you-go basis and a fully funded individual account system known as the Premium Pension System (PPS). The contribution rate to the overall system

¹Studies analyzing the costs of flows and fire sales include Chordia (1996), Greene and Hodges (2002), Alexander, Cici, and Gibson (2007), Christoffersen, Evans, and Musto (2007), Chen, Goldstein, and Jiang (2010).

is 18.5%; 16% is paid to the notional defined contribution segment, while 2.5% is credited to the funded individual accounts of the PPS. In addition, a means-tested benefit provides a minimum pension.²

We study the activity and performance of individual investors in the PPS. The system functions like a national 401(k) plan. Participation is mandatory and the coverage is universal. By 2010 the system included more than six million individuals and more than SEK 350 billion were under management. The Swedish Pensions Agency administers the system, but it is up to individual participants to select how to invest their funds. The system is sometimes referred to as the PPM system, after the acronym of the previous agency handling the system.

The investment options offered to individual participants in the PPS are a subsample of the mutual funds offered to retail investors. In 2000, at the time of the first fund selections, approximately 450 funds were registered; in 2010 it was around 780 funds. During the period there have been about 1,230 funds offered. Most funds are equity funds, about half of which invest primarily in international equities. Individuals may choose up to five funds and can change their allocations on a daily basis at no additional cost. The government established in 2000 a default fund for individuals who do not make an active investment choice. The default fund has invested in stocks and bonds to achieve high long-term returns with low overall risk. The default fund became a life-cycle fund in May 2010.

Information about the funds in the PPS is presented on the agency's website and in a catalogue distributed to participants on request. The funds are listed by type, for example, fixed income, balanced, life-cycle, and equity funds, and for each fund there is information such as the rate of return and risk (measured over several different horizons), the fee and

²Sweden's Premium Pension System is also described in Cronqvist and Thaler (2004) and Palme, Sundén, and Söderlind (2007). Klevmarken (2002) provides a concise background to the Swedish pension reforms of the 1990s and explains the structure of the new system. Sundén (2006) discusses the experience with the pension reforms.

the major holdings.

Fund managers charge the same management fees to pension investors as they do to retail investors. Because account administration is handled by the Swedish Pensions Agency, fund managers must rebate a share of their fees to them, which passes this rebate through to the individuals. In 2010, the asset-weighted average fund fee after the rebate was 0.37% of assets for active investors and 0.15% for those in the default fund. The Swedish Pensions Agency charges a fixed administration fee to all participants; it was 0.16% of assets in 2010. Effectively, the typical fee in the pension system is lower than in the retail market.

3 Data and benchmarks

We have novel data from the Swedish Pensions Agency on more than six million individual investors and all offered mutual funds in the Premium Pension System (PPS). For each individual we have the initial fund choices and all fund changes on a daily basis. We construct individuals' portfolios, day by day, and compute their returns from the portfolio weights and fund returns. From the population we randomly draw 100,000 individuals. Out of these, we consider 70,755 individuals that were in the system when it was launched in September 2000 and stayed in it until May 2010. This sample selection procedure avoids tricky issues of how a changing sample composition could affect the results. For example, it does not generate endogeneity problems as the only way out of the sample is to retire at the statutory age, become disabled or die (none of them the likely result of an individuals deliberate choice).

We are particularly interested in the information on the individuals' returns and the number of fund changes (excluding changes carried out by PPS when a fund is discontinued or replaced by another). In addition to the fund choices and fund changes, we know the gender and age of each individual. We also know their pension rights in year 2000, which we use as a proxy for income.

The fund data cover all funds offered to pension investors during the sample period. They cover not only the funds available today, but also the funds that have been terminated or taken out of the system. Hence, our sample is free from survivorship and backfill biases. We consider returns, net of fund management and pension administration fees, to reflect actual investor experience. Returns are also adjusted to reflect the effect of the fee rebates that the Swedish Pensions Agency negotiates on behalf of pension investors. The information necessary to make these adjustments (i.e., fund management fees, administration fees, and fee rebates) is obtained from the agency.

We obtain risk-adjusted performance measures (alphas) in standard performance evaluation regressions as further described in Section 4. We initially consider three benchmark factors: the excess return of the Swedish equity market (Affärsvärldens generalindex); the excess return of the world equity market (MSCI world investable index in SEK); and the excess return of the Swedish bond market (OM benchmark total for the Swedish long bond index). Excess returns are constructed by subtracting a proxy for the risk-free rate (JP Morgan's one-month cash rate for Sweden). These benchmark factors are obtained from Datastream. The alphas are the intercepts in the performance regressions on daily returns and are annualized by multiplying them by 252 (approximately the number of trading days in a year). We also consider benchmarks related to value/growth and momentum. Our choice of factor benchmarks does not affect the results significantly; we elaborate on this later.

Since the mid naughties an industry of financial advisors has emerged. The financial advisors make recommendations as well as manage portfolios on a discretionary basis. To distinguish portfolios managed by individuals (non-coordinated investors) and financial advisors (coordinated investors) we apply a simple algorithm to the full population of more than six million individuals. We classify an individual as being coordinated if the following two conditions hold. First, the individual has done at least once exactly the same fund change

(same fund origin and destination) as 999 or more other individuals. Second, the individual has done for at least one fifth of the fund changes exactly the same change as nine or more other individuals. Using this approach we find that around 10% of the population has made coordinated fund changes. In our sample we have 8,115 coordinated investors and 62,640 non-coordinated investors. We experimented with alternative classification algorithms, with no significant changes in the resulting selection.

We view the coordinated investors as individuals who resort to financial advisors. We focus on the non-coordinated investors though we make some comparisons between coordinated and non-coordinated investors.

4 Estimation methods

We report results from the traditional calendar time approach (see, for example, Fama, 1998). To implement it, the investors are sorted into M non-overlapping categories based on the number of fund changes (1 change, 2–5 changes, etc.). For category j , let \bar{r}_{jt} be the cross-sectional average of the excess returns in period t . We then estimate the following SURE system with OLS:

$$\bar{r}_{jt} = \alpha_j + \beta_j' f_t + u_{jt}, \text{ for } j = 1, \dots, M, \quad (1)$$

where f_t is a vector of excess returns on benchmark factors. We test if the alpha of category j is different from zero, or if it different from another category's alpha, using a Newey and West (1987) estimator of the covariance matrix of the full system. This approach is known to have good statistical properties as long as the number of categories is small. However, when we want to control for several investor characteristics like age, income and gender, the sorting into categories becomes an issue.

To overcome this problem, we apply a panel method ($t = 1, \dots, T$ and $i = 1, \dots, N$) to estimate a factor model:

$$r_{it} = (\alpha + \alpha'_z z_i) + (\beta + \beta'_z z_i)' f_t + \varepsilon_{it}, \quad (2)$$

where r_{it} is the excess return for individual i in period t and where we condition on the investor characteristics z_i . Note that the factors are the same for all investors and that the investor characteristics are here assumed to be constant across time. Allowing for time-varying investor characteristics is straightforward. This panel regression nests several other methods.

Consider the case when there are only two categories and z_i is a dummy variable indicating membership of category two. Regression (2) is then:

$$r_{it} = \begin{cases} \alpha + \beta' f_t + \varepsilon_{it} & \text{for } i \in \text{category 1} \\ (\alpha + \alpha_z) + (\beta + \beta_z)' f_t + \varepsilon_{it} & \text{for } i \in \text{category 2.} \end{cases} \quad (3)$$

This is the same as the calendar time approach, since it effectively estimates a separate regression for each of the two categories. The extension to many categories/dummy variables is straightforward.

More generally, let z_i be a vector of variables measuring investor characteristic, for instance the number of fund changes, age and income. In this case, Hoechle, Schmid, and Zimmermann (2009) show that the point estimates of α_z in regression (2), which measure how performance depends on the investor characteristics, are the same as those from a commonly applied cross-sectional regression approach. In such a cross-sectional regression approach there are two steps. First, estimate a factor model for each investor, $r_{it} = \alpha_i + \beta'_i f_t + \varepsilon_{it}$. Second, run a cross-sectional OLS regression of the estimated alpha on the vector of investor characteristics, $\hat{\alpha}_i = z'_i \gamma + v_{it}$. In typical applications, the standard errors of the

coefficients in the second step do not account for any cross-sectional correlation of the error terms (including those caused by the estimation errors of the alphas). Hoechle, Schmid, and Zimmermann (2009) argue that Driscoll and Kraay (1998) standard errors of the panel method can account for such cross-sectional correlations. In a Monte Carlo experiment we find that the Driscoll-Kraay method is indeed a good choice in this context, whereas both White's (1980) method, and a standard cluster method have problems. We describe and report the results of our experiment in the Appendix.

5 Results on non-coordinated investors

In this section we report results on non-coordinated investors. These are investors who choose and change funds themselves and most likely do not resort to financial advisors. (In later sections we consider coordinated investors.) We begin by documenting the activity of individuals. We then evaluate their performance and relate it to their activity. We also establish causality from activity to performance. Finally, we shed light on the type of fund changes that generate performance.

5.1 Investor activity

We categorize all individuals according to how many fund changes they have made to their portfolios. This is our measure of activity. There are two categories for individuals who have never made a fund change: the default fund category refers to individuals who have been in the default fund for the entire sample period; the no change category refers to individuals who have made an active fund choice when the system was launched, but who have not made a fund change since. The remaining categories are of individuals who have made a fund change at least once.

The first column in Table 1 presents the percentage of individuals in the various investor

categories (of a total of 62,640 non-coordinated investors). We document strong evidence of inertia in fund choices.³ Approximately 69% of the individuals in our sample have not made a fund change at all during the 2000-2010 period: 30.2% have been in the default fund for the entire sample period, and 39.0% have initially been active and chosen one or several funds but have not made a fund change since. In the active investor categories, 16.0% have made a fund change once; 9.2% made between 2 and 5 changes; 4.1% between 6 and 20; 1.2% between 21 and 50; and 0.3% more than 50 changes. The small number of fund changes is consistent with previous evidence of low activity in pension accounts, but is somewhat surprising as these retirement accounts have no transaction costs (see Agnew, Balduzzi, and Sundén, 2003, and Choi, Laibson, and Metrick, 2002, for discussions).

In further analysis (not tabulated) we find several other interesting patterns. The typical portfolio reallocation involves almost 50% of the old portfolio. In more than 40% of the fund changes, individuals invest in the same asset class (equity, fixed income, balanced funds or generation funds) and in less than 10% of the changes individuals invest in completely different asset classes. It appears that men change funds more frequently than women do (for instance, in the highest activity category 66% are men), as do high income individuals (pension rights for individuals in the highest activity category are on average 23% higher than those of individuals in the passive category), while age is unrelated to the number of fund changes.

5.2 Investor performance

Individuals are often regarded as unsophisticated investors. Odean (1998, 1999) and Barber and Odean (2000) document poor average performance of individual investors relative to institutions and to the market. However, Coval, Hirshleifer, and Shumway (2005) find that

³Madrian and Shea (2001), Choi, Laibson, Madrian, and Metrick (2002), Agnew, Balduzzi, and Sundén (2003) and Mitchell, Mottola, Utkus, and Yamaguchi (2006) report similar results.

not all individual investors do poorly in their investments, and that there is strong persistence in their performance. Further, Avery, Chevalier, and Zeckhauser (2009) provide evidence that stock picks by individuals are informative about future stock prices. We find that individuals who are more active in the pension system, as measured by the number of fund changes, outperform passive investors and common market benchmarks. Active investors earn higher returns without necessarily taking more risks, and as a result their portfolios exhibit greater alphas and Sharpe ratios.

Table 1 presents the relation between the number of fund changes and performance for the various investor categories. We follow the calendar time portfolio approach, and form an equally weighted portfolio for each activity category and report the performance of those portfolios. The average returns are increasing in the number of fund changes. For example, the average return is less than 2% per year for passive investors and more than 8% per year for the most active investors. These higher average returns are obtained without any significant increase in volatility, resulting in distinctly greater Sharpe ratios. Alphas from a three-factor model using the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market as factors, are also greater for more active investors. For instance, individuals in the most active category have an annualized alpha that is 7.1% higher than individuals in the passive category outside the default fund. Patton and Timmermann's (2010) test of a monotonous relationship and a t-test of the difference between the most and least active categories indicates that the results are not only economically but also statistically significant. It can be shown that the results are robust to the inclusion of other factors. For example, adding US momentum or value/growth factors has little effect on the results (Asness, Moskowitz, and Pedersen, 2009, find that momentum and value factors are correlated across markets and asset classes).

Table 1 presents the performance of two categories of passive investors: those who made an active fund choice when entering the pension system in 2000 but no subsequent changes

and those who did not make an active initial choice and were thus assigned the government-managed default fund. Individuals in the default fund obtain an alpha that is 0.40% higher per year than that of passive investors, although it is not statistically significant at usual levels.

Our results are illustrated and strengthened using box plots of alphas obtained from performance regressions of individuals' portfolios in Figure 1. The central mark in a box is the median of the cross-sectional distribution (with the notch indicating a 95% confidence interval); the edges are the 25th and 75th percentiles and the whiskers indicate the most extreme data points not considered outliers. The medians are close to the means in Table 1 and show the same pattern across categories: higher activity is associated with greater alphas. The 25th and 75th percentiles indicate the same pattern. This suggests that activity is associated with a robust upward shift of the entire cross-sectional distribution of alphas.

To further assess the statistical significance of our results and control for other variables that could affect performance, we use the Hoechle, Schmid, and Zimmermann (2009) panel data regression approach together with the Driscoll and Kraay (1998) covariance estimator (accounting for heteroskedasticity as well as cross-sectional and serial correlations in the error terms). Table 2 presents these results. As discussed in Section 4, the panel data approach is a natural extension of the calendar time approach. For instance, when the investor characteristics are described by a set of dummy variables and the panel is balanced, the panel data regression yields the same point estimates as the calendar time approach. The results in specification I, (where individuals' returns are regressed on a constant and a set of dummies for the activity category) are very similar to those reported in Table 1. The most active category has a 7.1% higher alpha than the passive category (captured by the constant). In addition, the results indicate that the performance differences are also statistically significant when controlling for cross-sectional and serial correlations. Adding control variables (age, gender and an income proxy) does not change the main conclusion

on activity. Of these controls, the economically and statistically significant coefficient is the gender dummy. Controlling for activity and the other characteristics, it appears that men have a 0.3% higher alpha per year than women do.

Inspired by the observed relation between activity and performance, Table 2 also reports results from a panel data regression where the activity category dummies have been replaced by a single variable: the number of fund changes. The results indicate that ten additional fund changes are associated with a 1.1% higher alpha per year.

Overall our results provide strong evidence of a positive relation between activity and performance in the context of a pension system with no transaction costs. Active investors seem able to avoid poorly performing funds and take advantage of the system to persistently beat passive investors and common market benchmarks. This result contradicts the commonly held belief that the best thing individuals can do when it comes to managing their investments is... nothing.

5.3 Causality: Counterfactual returns

We have documented a positive relation between the number of fund changes and performance. However, the direction of causality is not self-evident. While we interpret the results as implying that changes lead to higher returns, alternative explanations are possible. It may be the case that some individuals change between well-performing funds, and that therefore it is not their activity that drives the performance. More generally, this relation between activity and performance may be due to common factor rather than causality. We now provide evidence that activity appears to lead to higher returns.

To investigate causality, we construct counterfactual portfolios by randomly discarding a certain percentage of active fund changes.⁴ Table 3 presents the performance that investors

⁴In constructing counterfactual portfolios, we keep track of the fund that investors are assigned to whenever a fund is removed from the PPS. This fund is most often another fund managed by the same fund management company or the default fund.

would have obtained if they had not executed some of their changes. Performance is poorer when fund changes are discarded. For instance, we estimate an alpha of 3.44% per year for individuals in the 21-50 fund changes category. This alpha decreases to 1.93% per year when 25% of the fund changes are kept (75% are discarded) and to -0.17% per year when no fund changes are kept. This indicates that the fund changes are instrumental in the higher performance of active investors.

The last column of Table 3 presents the performance that individuals would have achieved if they had remained with their initial fund choice. The most active investors would have outperformed the least active investors by 0.9% per year, suggesting that individuals in the most active categories made better initial fund choices. However, this outperformance is much smaller than the 7.1% difference per year in actual alphas, and it is not statistically significant at usual significance levels.

One may speculate as to why some individuals are more inclined than others to devote time and effort to actively managing and monitoring their pension accounts. One possibility may be that some investors simply have more financial knowledge than others.⁵ Irrespective of the ultimate source of the observed differences in performance, our key result is that active investors would not outperform less active investors without making fund changes.

5.4 How does activity lead to greater performance?

On average, individuals replace half of their portfolios when changing funds and most changes are between funds in the same asset class. However, there is substantial variation across individuals, and the way they change funds seems to affect their performance. We now

⁵A number of demographic and occupational variables may be important for financial decisions and risk-taking. Interestingly, Grinblatt, Keloharju, and Linnainmaa (2010) find that stock market participation and IQ are related, and Grinblatt, Keloharju, and Linnainmaa (2011) document that IQ is a significant driver of investor performance. Further, Barnea, Cronqvist, and Siegel (2010) and Cesarini, Johannesson, Lichtenstein, Örjan Sandewall, and Wallace (2010) link genetic variation to differences in financial decision-making. Calvet and Sodini (2011) investigate the determinants of financial risk-taking, controlling for genes.

consider the effects of fund selection, market-timing, and momentum and contrarian changes.

We study market timing by constructing counterfactual returns where changes across asset classes are discarded. For instance, a change from an equity fund to a fixed income fund is excluded, while a change between two equity funds is included. Similarly, we study fund selection by constructing counterfactual returns where all changes within an asset class are discarded. Note that market timing and fund selection changes do not add up to 100%, as we only consider pure changes. Table 4 presents the results. Market-timing changes seem to have little effect on performance. The difference in alphas with and without market-timing changes is small and never statistically significant at usual levels. This result is in line with Agnew, Balduzzi, and Sundén (2003) and Choi, Laibson, and Metrick (2002), who argue that pension investors do not have market-timing abilities. In contrast, fund selection changes appear to be crucial for performance and they are much more common than market-timing changes. The difference in alphas with and without fund selection changes is significant for the most active categories. These findings suggest that the superior performance of active investors is partly driven by fund changes within the same asset class.

We study momentum and contrarian changes by again constructing counterfactual returns. We define a momentum change as a change in which the new fund outperformed the old fund in the previous six-month period. Similarly, a contrarian change is a change to a fund that underperformed in the previous six-month period. Table 5 presents the results. The difference in alphas with and without contrarian changes is small and never significant. However, when the more common momentum changes are excluded, performance decreases for all categories. In absolute terms, the difference in alphas is greater for the more active investor categories. The better performance of active investors appears to be the result of changing to funds with better recent performance that continue to outperform their peers. Our results at the individual level are consistent with the smart money effect documented at the fund level by Gruber (1996) and Zheng (1999).

We also consider performance models augmented with a fund momentum factor built from fund returns (the average return of the 25% of funds with the highest returns over the past 12 months in excess of the risk-free return).⁶ Untabulated results show that the loadings of active portfolios on this factor increase with activity. The difference in the alphas between the most active and least active investor categories is smaller than in the three-factor model, but is still 5% per year and significantly different from zero. The returns obtained by the most active category are about the same as the returns that could have been obtained by pursuing the best (ex-post, with the benefit of hindsight) fund momentum strategy we identify.

Overall, these results suggest that active investors pursue momentum-like strategies, and that those strategies may be the reason for their superior performance. Importantly, these momentum strategies would most likely be quite costly outside the pension system. To what extent this activity imposes a burden on less active investors will be investigated later.

6 Results on coordinated investors

In this section we report results on coordinated investors. We attribute coordinated changes to financial advisors who give recommendations and manage portfolios on a discretionary basis. This identification is not arbitrary. Our demanding classification algorithm, casual observations, and conversations with officers at the Swedish Pensions Agency suggest that a strong link exists between coordinated fund changes and financial advisors.⁷

Table 6 presents the activity and performance of coordinated investors. The first column reports the percentage of individuals in the various activity categories (out of 8,115 total

⁶We also experiment with one-month, three-month and six-month momentum factors with similar results. We do not include a short losers portfolio in the momentum benchmark because funds cannot be shorted.

⁷Conversations with officers at the Swedish Pensions Agency reveal that web-based coordinated changes are frequent and often executed from a single IP address. The changes often involve individuals from similar geographical or age groups. Reassuringly, our algorithm seems to deliver estimates of the number of individuals on an advisory relation similar to those independently reported by the authority.

coordinated investors). Coordinated investors are much more active than non-coordinated investors. For example, approximately 33% of coordinated investors made more than 20 changes, whereas less than 2% of non-coordinated investors were equally active. Coordinated investors represent only a small part of the total population (approximately 10% of the population in 2010), but account for a disproportionately large share of the fund changes in the system (approximately 80% of all changes in 2010).

Table 6 also presents performance results for portfolios of coordinated investors. Individuals are included in the portfolios during the time period we classify them as coordinated.⁸ The average returns are mildly increasing in the number of fund changes for the first three categories of coordinated investors, with a major increase for the highest activity category. Alphas follow a similar pattern. Coordinated investors with 21-50 changes obtain an annualized alpha that is only 1.1% higher than that obtained by investors making 2-5 changes (our least active category of coordinated investors). The most active category has an annualized alpha that is 4.4% higher than the least active category. It appears that coordinated investors also benefit from being more active. The test of a monotonous relationship and a t-test of the difference between the most active and least active categories support this conclusion. Untabulated results based on a linear panel regression specification indicate that an extra coordinated change leads to an increase in performance of about 0.05% per year and is driven by the most active coordinated investors. It is worthy of note that the effect is half of that found for non-coordinated investors.

Overall, individuals who resort to financial advisors do not seem to perform better than those who manage their retirement accounts themselves or who are assigned to the default fund. With the exception of the highest activity category, coordinated investors' portfolios have pre-fee alphas close to zero. Financial advisors often charge 1%-2% of assets under

⁸The results are very similar when we consider coordinated investors over the entire sample period, and not only for the period they are classified as coordinated.

management per year, which would significantly lower the post-fee alphas.

A natural role for financial advisors is to sell information or monitor pension fund accounts. In the PPS setting, another role would be to better exploit the advantages given to active investors, namely, no transaction costs for changing funds. Whether they undertake these roles effectively is an open question. A literature on financial advisors has recently emerged. Mullainathan, Nöth, and Schoar (2010) find that advice likely exaggerates existing behavioral biases. The evidence provided by Bhattacharya, Hackethal, Kaesler, Loos, and Meyer (2011) and Hackethal, Haliassos, and Jappelli (2011) suggests that advised investors do not achieve superior investment performance.

7 Externalities of activity

Individual investors in the PPS can change their allocation of funds on a daily basis at no cost. We have provided evidence that active investors manage to obtain superior returns. We want to explore whether this happens, at least to some extent, at the expense of other investors in the system. We therefore consider the direct effects of outflows on the performance of a fund and thereby on other investors.⁹

To assess the effects of outflows on fund performance, we run regressions of a fund's abnormal return on its lagged abnormal returns and various measures of outflows:

$$ar_{it} = \alpha_i + \beta_0 outflow_{it} + \sum_{k=1}^3 \beta_k ar_{it-k} + \epsilon_{it}, \quad (4)$$

where ar_{it} is the daily abnormal return of fund i at day t and $outflow_{it}$ is a measure of the fund's outflow. The abnormal return of a fund is obtained from a three-factor performance regression using the excess returns of the Swedish stock market, the Swedish bond market,

⁹We have also considered the effects of inflows on performance. We have not found economically significant effects of inflows that are robust across various specifications.

and the world stock market as factors. The abnormal return is defined as the sum of the intercept and the residual in that regression. The abnormal return and outflow seem contemporaneous in this specification. However, it is important to note that the decision to make a fund change is taken two to three days before the actual flow occurs. This means that even if the outflow is contemporaneous, it is driven by decisions taken previously, making reverse causality explanations unlikely. The regression model is estimated by pooling all data and including fund fixed effects. Effectively, we only use the time series to identify the return-outflow relationship (similar to Chen, Goldstein, and Jiang, 2010). It is crucial that standard errors account for the cross-sectional correlations in the error terms. We therefore use the spatial estimator by Driscoll and Kraay (1998) for the panel.

Table 7 presents the results for equity funds over the 2000 to 2010 period. The outflow measure in specification I is the outflow from a fund, expressed in terms of 1,000 fully invested individuals. The point estimate in this specification indicates that an outflow of 1,000 individuals leads to an immediate reduction in a fund's net asset value of 0.11%. Specifications II-IV use a dummy variable (one if the outflow from a fund is above a threshold, and zero otherwise) as an extreme outflow measure. The three thresholds are 100, 300, and 500. The point estimate of approximately -0.25 in specification III means that the immediate effect of an extreme outflow from a fund is a decline in its net asset value of about 0.25%. This effect is smaller for a less extreme outflow and greater for a more extreme outflow. Extreme outflows happen in 0.266%, 0.093%, and 0.059% of the observations in specifications II-IV. This means that the extreme outflows for a fund in specification III occur roughly on one day out of 1,000 days.

The outflow measures above are based on absolute flows and do not take into account the number of investors in a fund and their assets, nor the typical outflow from the fund. We therefore run complementary regressions with two relative outflow measures. In specification V, we consider the absolute outflow from a fund in relation to its total assets in the pension

system. In specification VI, we consider the absolute outflow from a fund in relation to its average outflow. The coefficients on both measures are negative and statistically significant at the 5% and 1% levels. The point estimates of about -0.77 in specification V can be interpreted as follows: If 10% of the pension investors redeem their investments in a fund (leaving the remaining pension investors and the retail investors), the effect is a decline in net asset value of about 0.077% for that fund.

We are interested in understanding the full dynamics of performance and flows. It is common for extreme outflows to cluster and occur two or more days in a row. For example, outflows of 300 or more fully invested individuals occur 290 times 2 days in a row, 82 times 3 days in a row, 35 times 4 days in a row, and 14 times 5 days in a row. We therefore estimate one more panel system for outflows and take into account the correlations between the two panels. Combining them, we can construct a recursive VAR, which enables us to compute impulse response functions of shocks. A panel VAR of this kind constructs the error terms in each regression equation to be uncorrelated with the error terms in the preceding equation. The identifying assumption is that flows on day t (but determined by the pension investors two to three days earlier) affect the abnormal returns at day t , but abnormal returns affect flows with a lag of at least one day.

We consider impulse response functions of a shock to the outflow variable. Figure 2a depicts the effect of a one-unit shock in the outflow (1,000 fully invested individuals leaving the fund) on current and future outflows. Outflows tend to increase over the next ten days and stabilize at 1.35 (i.e., at 1,350 fully invested individuals). Figure 2b depicts the effect of an outflow on returns. The cumulative effect indicates that after ten days, the fund affected by this adverse shock has a 0.18% lower net asset value than otherwise. The confidence bands for the impulse response functions in the figures are based on a block bootstrap simulation with 3,000 repetitions, allowing for spatial correlation across funds.

These results provide evidence that frequent fund changes, with no cost for the active

investor, induce costs borne by the system as a whole. There are administrative and trading costs for the Swedish Pensions Agency and the funds. Furthermore, the extreme outflows can force funds to trade at unfavorable prices. Edelen (1999), Karceski, Livingston, and O’Neal (2004), Edelen, Evans, and Kadlec (2007) and Coval and Stafford (2007) discuss and measure how redemptions can trigger transaction costs and fire sales that affect valuations.¹⁰ The costs are borne by the system as a whole and shared by all investors (active or passive). Some of these costs are likely exacerbated by financial advisors, who are very active and the drivers of the extreme outflows.

8 Concluding comments

We document strong evidence of inertia among Swedish pension savers. This inactivity is usually a concern for pension authorities and has at times prompted pension designers to adopt measures to encourage individuals to become active investors. Our results suggest that it is costly for individuals to disengage from managing and monitoring their pension assets in a modern defined contribution plan. Our results also suggest that activity benefits the individual investor, whereas extreme outflows from mutual funds affect funds’ net asset values negatively for all investors.

We consider detailed data of individuals’ choices and changes of mutual funds in the Swedish Premium Pension System from 2000 to 2010. We find that active investors earn higher returns than passive investors. For example, the most active investors earn approximately 7% higher average returns than passive investors. As the difference in risk-adjusted returns is of a similar magnitude, the results are not due to risk compensation.

¹⁰A more subtle cost is the exclusion of illiquid investment options from the fund menu in the PPS. Consider an illustration of this issue. On September 8, 2008, the pensions agency had to liquidate a position of SEK 55 million in Danske Fund Baltic. In addition to have an impact on the value of the shares for the remaining shareholders, the fund manager claimed that it would be impossible to liquidate all those shares in the usual time span (two-three days for foreign funds). In the end, the transaction took one month to complete and the fund was later withdrawn from the system by Danske Bank.

The high activity of a minority of individuals seems to burden the pension system. There are several costs (e.g., administrative, trading, and liquidity provision) associated with the system, and active investors do not have to pay them. Financial advisors contribute to coordinated investments and redemptions and exacerbate these costs. Hence, measures designed to help individuals become active investors are not always beneficial. In fact, these measures may negatively impact the performance of inherently passive investors.

Finally, our results relate to important pension design issues: How much freedom should individual investors have to choose and change funds? Should all individuals be offered the same investment opportunities (given that their trading demands may differ)? Should financial advisors and account managers be restricted in their operations? We do not address all these issues, but given that pension systems are often designed for an average individual, the barbell of highly active and passive investors identified in this study may be undesirable in a pension plan.

Appendix: A Monte Carlo experiment

In this appendix we report results from a Monte Carlo experiment. We consider the model:

$$r_{it} = \alpha + \beta f_t + \gamma g_i + \varepsilon_{it},$$

where r_{it} is the return of individual i in period t , f_t is a benchmark return and g_i is the demeaned number of the cluster (or category) that the individual belongs to. This is a simplified version of the regressions we run in the paper. We are particularly interested in γ , which measures how investor performance depends on investor activity.

The experiment uses 3,000 artificial samples with $t = 1, \dots, 2,000$ and $i = 1, \dots, 1,665$. Each individual is a member of one out of five equally sized clusters (333 individuals in each cluster). The benchmark return f_t is IID normally distributed with a zero mean and a standard deviation equal to $15/\sqrt{250}$. The error term ε_{it} is normally distributed with a zero mean and a standard deviation of one, and we consider different cross-sectional correlations. In generating the data, we let the true values of α and γ be zero, while β is one. These are also the hypotheses tested below. To keep the simulations easy to interpret, there is no autocorrelation or heteroskedasticity.

We report results for three different GMM-based methods: White's (1980) method, a cluster method, and Driscoll and Kraay's (1998) method. To keep the notation short, let the regression model be $y_{it} = x'_{it}b + \varepsilon_{it}$, where x_{it} is a $K \times 1$ vector of regressors. The least squares sample moment conditions are:

$$\frac{1}{TN} \sum_{t=1}^T \sum_{i=1}^N x_{it} \varepsilon_{it} = \mathbf{0}_K.$$

Standard GMM results show that the variance-covariance matrix of the coefficients ap-

proaches

$$\text{Cov}(\hat{b}) = \Sigma_{xx}^{-1} S \Sigma_{xx}^{-1},$$

when when $T \rightarrow \infty$ and where Σ_{xx} is the probability limit of $(1/TN) \sum_{t=1}^T \sum_{i=1}^N x_{it} x'_{it}$ and S is the covariance matrix of the moment conditions.

The three methods differ with respect to how the S matrix is estimated. Let $h_{it} = x_{it} \varepsilon_{it}$ and recall that M is the number of clusters. We then have:

$$\begin{aligned} S_W &= \frac{1}{T^2 N^2} \sum_{t=1}^T \sum_{i=1}^N h_{it} h'_{it}, \\ S_C &= \frac{1}{T^2 N^2} \sum_{t=1}^T \sum_{j=1}^M h_t^j (h_t^j)', \text{ where } h_t^j = \sum_{i \in j} h_{it}, \\ S_{DK} &= \frac{1}{T^2 N^2} \sum_{t=1}^T h_t h_t', \text{ where } h_t = \sum_{i=1}^N h_{it}. \end{aligned}$$

To see the difference, consider a simple example with four individuals $N = 4$ and two clusters $M = 2$. Let individuals $i = (1, 2)$ belong to the first cluster and individuals $i = (3, 4)$ belong to the second cluster. The following matrix shows the outer product of the moment conditions of all individuals for a given t . White's estimator sums up the cells on the principal diagonal, the cluster method adds the underlined cells, and Driscoll and Kraay's method adds also the remaining cells:

$$\begin{bmatrix} i & \underline{1} & \underline{2} & \underline{3} & \underline{4} \\ \underline{1} & h_{1t} h'_{1t} & \underline{h_{1t} h'_{2t}} & h_{1t} h'_{3t} & h_{1t} h'_{4t} \\ \underline{2} & \underline{h_{2t} h'_{1t}} & h_{2t} h'_{2t} & h_{2t} h'_{3t} & h_{2t} h'_{4t} \\ \underline{3} & h_{3t} h'_{1t} & h_{3t} h'_{2t} & h_{3t} h'_{3t} & \underline{h_{3t} h'_{4t}} \\ \underline{4} & h_{4t} h'_{1t} & h_{4t} h'_{2t} & \underline{h_{4t} h'_{3t}} & h_{4t} h'_{4t} \end{bmatrix}$$

Table 8 reports the fraction of times the absolute value of a t-statistic for the true null hypothesis is higher than 1.96 (a nominal size of 5%). The table has three panels for different

correlation patterns of the error term ε_{it} .

Panel A reports simulation results where the error terms are IID. In this case all three methods have the right rejection rates, around 5% (the nominal size).

Panel B reports results where the error terms are correlated within each of the five clusters but there is no correlation between individuals that belong to the different clusters. In this case the cluster method and the Driscoll and Kraay's method have the right rejection rates, while White's method gives much too high rejection rates (around 85%). The reason is that White's method disregards correlation between individuals and in this way underestimates the uncertainty about the point estimates. It is also worth noticing that the good performance of the cluster method depends on pre-specifying the correct clustering. Further simulations (not tabulated) shows that with a completely random cluster specification, unknown to the econometrician, gives almost the same results as White's method.

Panel C reports results where the error terms have no cluster correlations but all individuals are now equally correlated (similar to a fixed time effect). For the intercept α and the slope coefficient on the common factor β , Driscoll and Kraay's method still performs well, while the cluster and White's methods give too many rejections. The latter two methods underestimate the uncertainty since some correlations across individuals are disregarded. It is more complicated for the slope coefficient of the cluster number γ . Once again, Driscoll and Kraay's method performs well, but both the cluster and White's methods lead to too few rejections; that is, the uncertainty is overestimated. The reason behind this is the interaction of the common component in the residual with the cross-sectional dispersion of the cluster number g_i .

To understand this last result, consider a stylized case where $y_{it} = \gamma g_i + \varepsilon_{it}$, where $\gamma = 0$ and $\varepsilon_{it} = w_t$ so all residuals are due to an excluded time fixed effect. In this case, the matrix

above becomes:

$$\begin{bmatrix} i & \underline{1} & \underline{2} & \underline{3} & \underline{4} \\ \underline{1} & w_t^2 & \underline{w_t^2} & -w_t^2 & -w_t^2 \\ \underline{2} & \underline{w_t^2} & w_t^2 & -w_t^2 & -w_t^2 \\ \underline{3} & -w_t^2 & -w_t^2 & w_t^2 & \underline{w_t^2} \\ \underline{4} & -w_t^2 & -w_t^2 & \underline{w_t^2} & w_t^2 \end{bmatrix}$$

This follows from $g_i = (-1, -1, 1, 1)$ and since $h_{it} = g_i \times w_t$ we get $(h_{1t}, h_{2t}, h_{3t}, h_{4t}) = (-w_t, -w_t, w_t, w_t)$. Both White's method and the cluster method sums up only positive cells, so S is a strictly positive number. The cluster method relies on the assumption that the clusters used in estimating S correspond to the values of the regressor g_i . However, this overestimates the uncertainty since it is straightforward to demonstrate that the estimated coefficient in any sample must be zero. This is seen by noticing that at a zero slope coefficient, the corresponding moment conditions $\sum_{i=1}^N h_{it}$ is zero for all t , so there is no uncertainty about the slope coefficient. In contrast, Driscoll and Kraay's method adds the off-diagonal elements which are all equal to $-w_t^2$, giving the correct result of $S = 0$.

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Table 1: Investor activity and performance

	Individuals (%)	Mean (% per year)	Standard deviation (% per year)	Sharpe ratio	Alpha (% per year)
Default fund	30.2	1.75 (5.29)	15.59	-0.08	-0.42 (2.21)
No change	39.0	1.73 (5.38)	17.12	-0.08	-0.83 (1.92)
1 change	16.0	1.74 (5.42)	17.33	-0.08	-0.71 (1.97)
2– 5 changes	9.2	2.49 (5.54)	18.19	-0.04	0.13 (2.23)
6–20 changes	4.1	4.09 (5.53)	18.71	0.05	1.85 (2.64)
21–50 changes	1.2	5.81 (5.23)	18.27	0.15	3.44 (2.91)
51– changes	0.3	8.62* (5.13)	18.29	0.31	6.29* (3.22)
<i>t</i> test [<i>p</i> -value]		[0.01]**			[<0.01]***
<i>MR</i> test [<i>p</i> -value]		[0.12]			[0.08]*

The table presents the activity and performance of individuals in various investor categories. The categories capture how active individuals have been in Sweden’s Premium Pension System during the 2000 to 2010 period. The category “default fund” refers to individuals who have been in the default fund. The category “no change” refers to individuals who made a fund choice and have never made a fund change. The remaining categories are of individuals who have made one or more fund changes. All investors have been in the sample over the entire period. The first column presents the percentage of individuals in the categories. The remaining columns present the mean, standard deviation, Sharpe ratio, and alpha of the categories. These statistics are computed on daily returns of individuals’ portfolios during the sample period. The mean, standard deviation, and alpha are expressed in % per year. Alpha refers to the intercept in a three-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market as factors. Standard errors, robust to conditional heteroscedasticity and serial correlation up to four lags as in Newey and West (1987), are reported in parentheses. The *t* test refers to a test of equal means or alphas for the categories “no change” and “51–changes.” The *MR* test refers to Patton and Timmermann’s (2010) test of a monotonous relationship over the number of fund changes (excluding the default fund). The *p*-values of these tests are reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Investor activity, performance, and characteristics

	I	II	III	IV
Constant (no change)	-0.828 (1.915)	-1.384 (2.234)	-0.651 (1.948)	-1.274 (2.244)
1 change	0.117 (0.428)	0.125 (0.426)		
2– 5 changes	0.962 (0.935)	0.965 (0.929)		
6–20 changes	2.678 (1.645)	2.665 (1.641)		
21–50 changes	4.265** (2.120)	4.215** (2.114)		
51– changes	7.114*** (2.556)	7.124*** (2.551)		
Number of changes			0.113** (0.049)	0.112** (0.049)
Age		0.008 (0.008)		0.008 (0.008)
Gender		0.306*** (0.106)		0.308*** (0.106)
Income		-0.007 (0.025)		0.009 (0.031)
<i>R</i> -squared	0.550	0.551	0.550	0.551

The table presents the results of pooled regressions of an individual's daily excess return on return factors, and measures of individuals' fund changes and other characteristics. The return factors are the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market, and they are allowed to vary across the individuals' characteristics. For brevity, the coefficients on these return factors and results on default fund investors are not presented in the table. The measure of fund changes is either a dummy variable for an activity category (see Table 1) or a variable counting the number of fund changes. Other characteristics are the individuals' age in 2000, gender (one if man, and otherwise zero) or pension rights in 2000, which is a proxy for income. The constant term and coefficients on the dummy variables are expressed in % per year. The income variable is scaled down by 1,000. Standard errors, robust to conditional heteroscedasticity and spatial autocorrelations with four lags as in Driscoll and Kraay (1998), are reported in parentheses. The sample consists of 62,640 individuals followed daily over the 2000 to 2010 period. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Counterfactual alphas, excluding random fund changes

	Alpha with all changes (% per year)	Alpha with 50% changes (% per year)	Alpha with 25% changes (% per year)	Alpha with no changes (% per year)
No change	-0.83 (1.92)			
1 change	-0.71 (1.97)	-0.81 [0.61]	-0.84 [0.64]	-0.89 [0.64]
2– 5 changes	0.13 (2.23)	-0.16 [0.22]	-0.37 [0.25]	-0.70 [0.28]
6–20 changes	1.85 (2.64)	1.20** [0.03]	0.66** [0.04]	-0.45* [0.09]
21–50 changes	3.44 (2.91)	2.58** [0.03]	1.93** [0.03]	-0.17** [0.05]
51– changes	6.29* (3.22)	4.59*** [<0.01]	3.65*** [<0.01]	-0.01*** [<0.01]
<i>t</i> test [<i>p</i> -value]	[<0.01]***	[0.02]**	[0.04]**	[0.19]
<i>MR</i> test [<i>p</i> -value]	[0.08]*	[0.12]	[0.14]	[0.19]

The table presents alphas for individuals categorized according to the number of fund changes they have made. See Table 1 for the categories. It also presents counterfactual alphas, i.e., the alphas these investors would have obtained if they had only made 50%, 25% or 0% of the fund changes they actually made. The alphas are computed on daily returns of non-coordinated investors' portfolios during the 2000 to 2010 period, and expressed in % per year. Alpha refers to the intercept in a three-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market as factors. Standard errors, robust to conditional heteroscedasticity and serial correlation up to four lags as in Newey and West (1987), are reported in parentheses. The *p*-value of a test of the difference between the actual and a counterfactual alpha is reported in square brackets. The *t* test refers to a test of equal alphas for the categories “no change” and “51– changes.” The *MR* test refers to Patton and Timmermann's (2010) test of a monotonous relationship over the number of fund changes. The *p*-values of these tests are reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Counterfactual alphas, excluding market timing of fund selection changes

	Alpha (% per year)	Alpha w/o market timing (% per year)	Excluded changes (%)	Difference in alphas (% per year)	Alpha w/o fund selection (% per year)	Excluded changes (%)	Difference in alphas (% per year)
No change	-0.83 (1.92)						
1 change	-0.71 (1.97)	-0.56 (1.99)	27.7	-0.15 [0.39]	-0.99 (1.94)	40.8	0.28 [0.29]
2–5 changes	0.13 (2.23)	0.32 (2.26)	21.8	-0.18 [0.32]	-0.60 (1.99)	52.4	0.73 [0.13]
6–20 changes	1.85 (2.64)	1.70 (2.78)	23.1	0.15 [0.74]	0.61 (2.24)	58.7	1.24* [0.08]
21–50 changes	3.44 (2.91)	2.97 (3.02)	24.3	0.47 [0.45]	2.26 (2.50)	57.3	1.18* [0.08]
51– changes	6.29* (3.22)	5.77 (3.31)	23.2	0.52 [0.44]	3.77 (2.83)	57.3	2.52*** [<0.01]
<i>t</i> test [<i>p</i> -value]	[<0.01]***	[<0.01]***			[0.02]**		
<i>MR</i> test [<i>p</i> -value]	[0.08]*	[0.04]**			[0.28]		

This table presents alphas for individuals categorized according to the number of fund changes they have made. See Table 1 for the categories. It also presents counterfactual alphas, i.e., the alphas these investors would have obtained if they had not made market timing or fund selection changes. The alphas are computed on daily returns of non-coordinated investors' portfolios during the 2000 to 2010 period, and expressed in % per year. Alpha refers to the intercept in a three-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market as factors. Standard errors, robust to conditional heteroscedasticity and serial correlation up to four lags as in Newey and West (1987), are reported within parentheses. The number of excluded fund changes are given as a percentage of all fund changes. The table also presents the difference between actual and counterfactual alphas; a *p*-value from a test of the difference is reported in square brackets. The *t* test refers to a test of equal alphas for the categories “no change” and “51– changes.” The *MR* test refers to Patton and Timmermann's (2010) test of a monotonous relationship over the number of fund changes. The *p*-values of these tests are reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Counterfactual alphas, excluding momentum or contrarian fund changes

	Alpha (% per year)	Alpha w/o momentum (% per year)	Excluded changes (%)	Difference in alphas (% per year)	Alpha w/o contrarian (% per year)	Excluded changes (%)	Difference in alphas (% per year)
No change	-0.83 (1.92)						
1 change	-0.71 (1.97)	-0.94 (1.96)	65.4	0.23 [0.49]	-0.69 (1.98)	25.5	-0.02 [0.86]
2–5 changes	0.13 (2.23)	-0.60 (2.00)	77.7	0.74 [0.25]	0.15 (2.21)	19.4	-0.02 [0.80]
6–20 changes	1.85 (2.64)	0.34 (2.23)	73.2	1.51* [0.09]	1.79 (2.74)	26.0	0.06 [0.79]
21–50 changes	3.44 (2.91)	1.38 (2.41)	64.0	2.06* [0.06]	3.20 (3.14)	35.2	0.23 [0.67]
51– changes	6.29* (3.22)	2.58 (2.63)	57.9	3.70*** [<0.01]	5.47 (3.62)	41.3	0.81 [0.40]
<i>t</i> test [<i>p</i> -value]	[<0.01]***	[0.06]*			[0.03]**		
<i>MR</i> test [<i>p</i> -value]	[0.08]*	[0.24]			[0.09]*		

This table presents alphas for individuals categorized according to the number of fund changes they have made. See Table 1 for the categories. It also presents counterfactual alphas, i.e., the alphas these investors would have obtained if they had not made momentum or contrarian changes. The alphas are computed on daily returns of non-coordinated investors' portfolios during the 2000 to 2010 period, and expressed in % per year. Alpha refers to the intercept in a three-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market as factors. Standard errors, robust to conditional heteroscedasticity and serial correlation up to four lags as in Newey and West (1987), are reported in parentheses. The number of excluded fund changes are given as a percentage of all fund changes. The table also presents the difference between actual and counterfactual alphas; a *p*-value of a test of the difference are reported in square brackets. The *t* test refers to a test of equal alphas for the categories “no change” and “51– changes.” The *MR* test refers to Patton and Timmermann's (2010) test of a monotonous relationship over the number of fund changes. The *p*-values of these tests are reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Investor activity and performance—coordinated investors

	Individuals (%)	Mean (% per year)	Standard deviation (% per year)	Sharpe ratio	Alpha (% per year)
No change					
1 change					
2– 5 changes	21.7	1.78 (5.22)	15.04	−0.73	−0.73 (2.20)
6–20 changes	45.2	2.01 (5.01)	12.04	−0.37	−0.60 (2.22)
21–50 changes	30.8	2.90 (5.08)	14.05	0.15	0.40 (2.24)
51– changes	2.3	6.29 (4.88)	13.23	0.73	3.64 (2.93)
<i>t</i> test [<i>p</i> -value]		[0.03]**			[0.03]**
<i>MR</i> test [<i>p</i> -value]		[0.06]*			[0.08]*

The table presents the activity and performance of coordinated investors in various investor categories. The first column presents the percentage of individuals in the categories. The remaining columns present the mean, standard deviation, Sharpe ratio, and alpha of the categories. These statistics are computed on daily returns of individuals’ portfolios during the period they are classified as coordinated. The mean, standard deviation, and alpha are expressed in % per year. Alpha refers to the intercept in a three-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market as factors. Standard errors, robust to conditional heteroscedasticity and serial correlation up to four lags as in Newey and West (1987), are reported in parentheses. The *t* test refers to a test of equal means or alphas for the categories “2–5 changes” and “51– changes.” The *MR* test refers to Patton and Timmermann’s (2010) test of a monotonous relationship over the number of fund changes. The *p*-values of these tests are reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Performance and outflows

	I	II	III	IV	V	VI
	Absolute	Absolute	Absolute	Absolute	Relative I	Relative II
Outflow _{<i>t</i>}	-0.109** (0.049)				-0.768** (0.319)	-0.069*** (0.024)
Outflow _{<i>t</i>} > 100		-0.210*** (0.063)				
Outflow _{<i>t</i>} > 300			-0.246*** (0.081)			
Outflow _{<i>t</i>} > 500				-0.262** (0.108)		
<i>arr</i> _{<i>t-1</i>}	-0.167*** (0.010)	-0.167*** (0.010)	-0.167*** (0.010)	-0.167*** (0.010)	-0.167*** (0.010)	-0.167*** (0.010)
<i>arr</i> _{<i>t-2</i>}	-0.070*** (0.012)	-0.070*** (0.012)	-0.070*** (0.011)	-0.070*** (0.012)	-0.070*** (0.012)	-0.070*** (0.012)
<i>arr</i> _{<i>t-3</i>}	-0.021** (0.010)	-0.021** (0.010)	-0.021** (0.011)	-0.021** (0.010)	-0.021** (0.010)	-0.021** (0.010)
<i>R</i> -squared	0.031	0.031	0.031	0.031	0.025	0.031

The table presents the results of panel regressions of a mutual fund's daily abnormal return on measures of outflows. The abnormal return is obtained from a three-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market as factors. The abnormal return is defined as the sum of the intercept in the performance regression and the residual. The outflow measure in Specification I is the outflow of a fund (zero if it is an inflow); it is expressed in terms of the number of fully invested investors in a fund and labeled Absolute. Specifications II-IV use a dummy variable (one if the outflow of a fund is more than a threshold, and zero otherwise) as an extreme flow measure. The three thresholds are 100, 300, and 500. These thresholds imply that 0.266%, 0.093%, and 0.059% of the observations are non-zero. The outflow measures in specification V and VI are relative measures. In specification V it is the outflows of a fund in relation to its total assets in the Premium Pension System; it is labeled Relative I. In specification VI it is the absolute outflow of a fund in relation to its average outflow; it is labeled Relative II. All specifications also include three lags of the abnormal return variable. All specifications also include fund fixed effects but they are not tabulated. Standard errors, robust to conditional heteroscedasticity and spatial correlations as in Driscoll and Kraay (1998), are reported in parentheses. The sample includes all equity funds over the 2000 to 2010 period. Each specification includes a total of 1,213,517 observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Simulated size of different covariance estimators

	White (1980)	Cluster	Driscoll-Kraay (1998)
<u>A. No cross-sectional correlations</u>			
α	0.049	0.049	0.050
β	0.044	0.045	0.045
γ	0.050	0.051	0.050
<u>B. Within-cluster correlations</u>			
α	0.853	0.053	0.054
β	0.850	0.047	0.048
γ	0.859	0.049	0.050
<u>C. Within- and between-cluster correlations</u>			
α	0.935	0.377	0.052
β	0.934	0.364	0.046
γ	0.015	0.000	0.050

This table presents the fraction of rejections of true null hypotheses at the nominal size of 5% for three different estimators of the covariance matrix: White's (1980) method, a cluster method, and Driscoll and Kraay's (1998) method. The model of individual i in period t and who belongs to cluster j is $r_{it} = \alpha + \beta f_t + \gamma g_i + \varepsilon_{it}$, where f_t is a common regressor (iid normally distributed) and g_i is the demeaned number of the cluster that the individual belongs to. The simulations use 3,000 repetitions of samples with $t = 1, \dots, 2,000$ and $i = 1, \dots, 1,665$. Each individual belongs to one of five different clusters. The error term is constructed as $\varepsilon_{it} = u_{it} + v_{jt} + w_t$, where u_{it} is an individual (iid) shock, v_{jt} is a shock common to all individuals who belong to cluster j , and w_t is a shock common to all individuals. All shocks are normally distributed. In Panel A the variances of (u_{it}, v_{jt}, w_t) are $(1,0,0)$, so the shocks are iid; in Panel B the variances are $(0.67,0.33,0)$, so there is a 33% correlation within a cluster but no correlation between different clusters; in Panel C the variances are $(0.67,0,0.33)$, so there is no cluster-specific shock and all shocks are equally correlated, effectively having a 33% correlation within a cluster and between clusters.

Figure 1: Investor activity and performance

The figure depicts the median, interquartile range and 95% whiskers of alphas for various investor categories. Alpha refers to the intercept in a three-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, and the world stock market as factors. They are computed on daily returns of non-coordinated investors during the 2000 to 2010 period, and are expressed in % per year. The categories capture how active investors have been in Sweden's Premium Pension System. The category "default fund" refers to individuals that have been in the default fund. The category "no change" refers to individuals who initially made a fund choice and have then never made a fund change. The remaining categories are of individuals who have made one or more fund changes. All investors have been in the sample over the entire period.

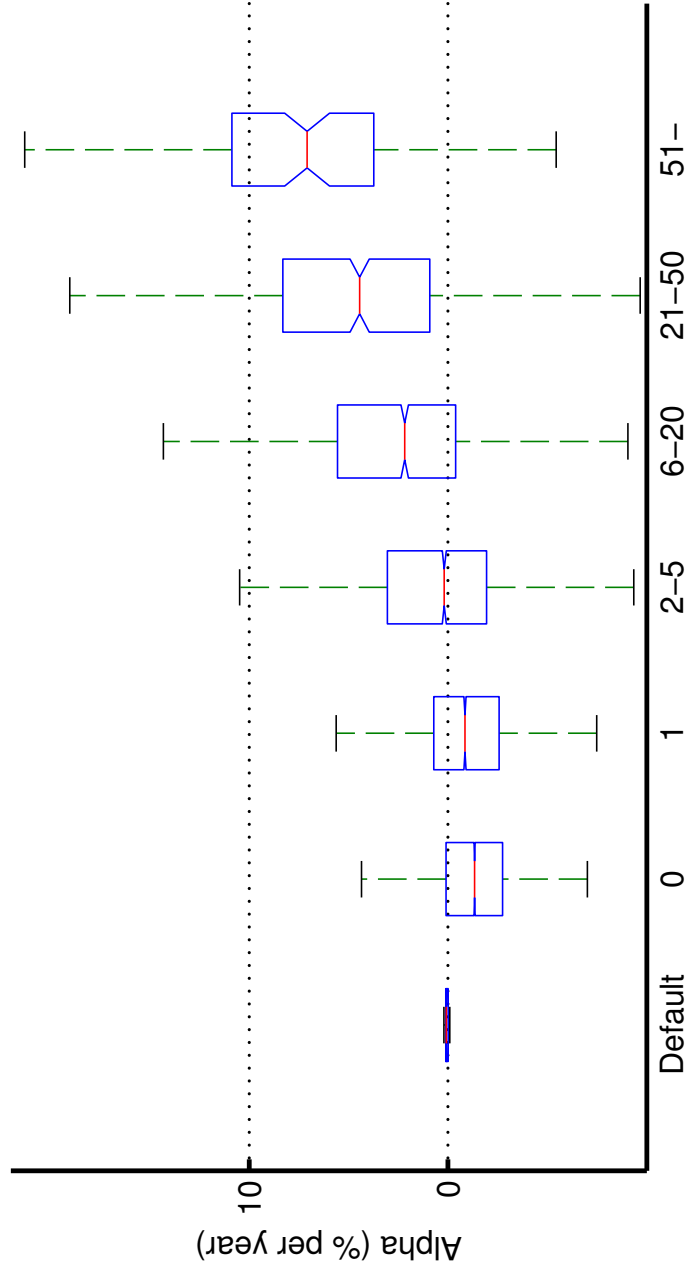


Figure 2: Impulse response functions for outflows and abnormal returns

The figure depicts the effect of a unit shock in the outflows on outflows and abnormal returns up to 14 days after the shock. Figure a depicts the effect on the outflows (red, solid line); Figure b depicts the effect on abnormal returns (blue, dashed line). The dotted lines are 90% confidence bands around the point estimates. The outflow shock is standardized to one. The abnormal return variable is expressed in %. The estimates are based on panel regressions of a mutual fund's daily abnormal return and outflows. The regression corresponds to specification I in Table 7, but augmented with a new panel regression to capture the dynamics in the outflow variable. The identifying assumptions are discussed in the text.

