Individual Investor Activity and Performance

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Abstract

We examine the daily activity and performance of a large panel of individual investors in Sweden's Premium Pension System in the period 2000 to 2010. We find that active investors outperform passive investors, and that there is a causal effect of fund changes on performance. Chosen funds outperform discarded funds over all the horizons we study. This outperformance is most significant for changes made within an asset class and towards funds with better recent past performance. While activity is beneficial for some individual investors, extreme flows out of mutual funds affect funds' net asset value negatively for all investors.

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1 Introduction

With assets under management projected to reach USD 13.7 trillion by the end of 2016, defined contribution plans are increasingly becoming the main source of retirement income worldwide.[1] These plans have many attractive features, such as portability and flexibility, but they place significant responsibility on individuals to make decisions and monitor their choices. Much to the concern of pension authorities, a wealth of evidence indicates, however, that most plan participants are not actively engaged in this process (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).

In this study we investigate whether there is any relation between individual investors' activity (inactivity) and portfolio performance in a modern defined contribution plan. We conduct our study using a detailed sample of Swedish pension savers that allows us to track the portfolios of more than six million individuals (the entire workforce of Sweden) in the Premium Pension System, and the daily changes they made, over a period of ten years. This allows us to investigate the activity and performance of pension investors in a system with a rich menu of investment options. We also investigate whether the activity of some pension investors affects other investors.

We find that investors who are actively involved in managing their pension accounts earn significantly higher returns than inactive 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% to 8.6% per year. The activity-performance relationship is monotonically increasing. Differences in risk-adjusted returns are of a similar magnitude, suggesting that higher returns are attributable to better investment performance rather than to risk compensation.

[1]This figure was reported by *Pensions and Investments*, May 13, 2013.

Active investors may simply be better educated or better informed, but a closer look at the differences in performance suggests that changing the funds in their portfolios is decisive to their outperformance. When we construct counterfactual returns by discarding fund changes, the differences in performance between active and inactive investors are much smaller. Similarly, when we look at the performance of portfolios formed based on the fund changes made by investors, similar to the transaction-based calendar-time portfolios considered by Seasholes and Zhu (2010), we find that the chosen portfolios outperform the discarded portfolios over all the horizons we study. For instance, the chosen portfolio returns exceed the discarded portfolio returns by an annualized 4.9% in the week following the portfolio change, and by 4.8% in the month following that change. These results cannot be attributed to investors that obtain higher returns subsequently deciding to be more active.[2]

The better performance of active investors is primarily the result of their changing funds within an asset class (fund-selection) rather than across asset classes (market-timing). This result is consistent with the findings 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 disproportionately choose past winners when making fund changes and that in doing so they (consciously or unconsciously) take advantage of short term persistence in fund performance (see Bollen and Busse, 2004) in a context where the absence of transaction costs makes it economical to do so. By comparison, inactive investors seem to remain invested in poorly-performing funds.

The picture emerging from our analysis is one in which pension investors who are inactive do worse than very active ones. This is not a foregone conclusion. Indirect evidence from

[2]Our results also indicate that individuals who are more active make marginally better initial fund choices. Based on their initial choice, the most active investors would have outperformed the least active investors by 1.0% per year. However, this outperformance is much smaller than the 7.4% difference per year in actual alphas.

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).[3]

Investors in the Premium Pension System can either change their retirement portfolios on their own or they can hire a financial advisor to help them to do so (i.e., they can be active by proxy). Many of the fund changes we observe in the sample are coordinated, which we attribute to financial advisors who give recommendations and manage portfolios on a discretionary basis. We analyze these investors separately. We estimate that coordinated investors accounted for 10% of the population, but executed 80% of all fund changes in 2010. Coordinated investors do marginally better than inactive individual investors on a gross-of-fees basis, but their outperformance vanishes and may even turn into mild underperformance once we deduct likely financial advisor fees. These differences are, however, hardly ever significant.

Our results also reveal a dark side to high levels of investor activity. Active investors force mutual fund managers to trade more, which can negatively impact fund returns. Since trading costs are borne by the fund, shareholders who trade implicitly impose a financial burden on others in the fund. This problem is likely aggravated by the presence of financial advisors who exacerbate trading demands, and the coordination of these demands. The sources of these costs vary: 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.[4]

[3]Individuals are often regarded as unsophisticated investors. Odean (1998 and 1999) and Barber and Odean (2000) document poor average performance of individual investors relative to institutions and to the market. However, as emphasized by Coval, Hirshleifer, and Shumway (2005), not all individuals do poorly in their investments.

[4]Studies analyzing the costs of flows and fire sales include Chordia (1996), Greene and Hodges (2002),

These costs can be large when there are no load, exit or redemption fees to dampen investor trading. Our results suggest that the costs created by active investors can be as high as 0.20% of a fund's assets under management for an extreme fund outflow, with financial advisors likely behind more than 90% of these flows.

Our paper contributes to the literature on individual investor behavior by investigating the relation between investor activity and portfolio performance in a modern defined contribution plan. Previous work on the relationship between activity and performance, including the influential work of Barber and Odean (2000 and 2002), has tended to focus on brokerage accounts. The evidence in the pension context has so far been limited and only indirect (Agnew, Balduzzi, and Sundén, 2003, and Choi, Laibson, Madrian, and Metrick, 2002). Our paper not only shows that inactive investors do worse than active ones in the setting we analyze, but it also suggests that the outperformance of highly active investors is, to some extent, obtained at the expense of buy and hold investors, highlighting a dark side to investor activity.[5] The study also contributes to the literature on the performance persistence in mutual funds by presenting evidence of a group of investors exploiting the kind of short term persistence in fund returns identified by Bollen and Busse (2004). In doing so it also presents evidence that active investors in the system are, on average, "smart" in the sense of generally being able to choose funds that outperform during their holding period.[6] Finally, the paper also considers the role of financial advisors (which have received plenty of attention lately, see for instance: Inderst and Ottaviani, 2012; Mullainathan, Nöth, and Schoar, 2012; Bhattacharya, Hackethal, Kaesler, Loos, and Meyer, 2012; and Hackethal, Haliassos, and Jappelli, 2012; Gennaioli, Shleifer, and Vishny, 2014) and highlights a consequence of

Alexander, Cici, and Gibson (2007), Christoffersen, Keim, and Musto (2008), Chen, Goldstein, and Jiang (2010).

[5]This result is broadly in line with the observations of Edelen (1999) and Johnson (2004) on mutual funds; see also Karceski, Livingston, and O'Neil (2004), and Edelen, Evans and Kadlec (2007).

[6]This is difficult to do with only aggregate data and without precise knowledge of when investors buy and sell their shares.

their activity which has been so far overlooked: the coordination they induce in individuals' trading demands.

The rest of the paper is organized as follows. Section 2 describes the Swedish Premium Pension System. The data and benchmarks used in the study are outlined in Section 3. Section 4 presents the main results on the activity and performance for individual and coordinated investors. Section 5 explores whether extreme investor induced flows affect pension funds' net asset values and thereby other investors. Section 6 concludes.

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 is 18.5% of the gross income of an individual; 16% is paid to the notional defined contribution segment, while 2.5% is credited to the funded individual accounts of the PPS. Contributions are capped at 7.5 times the income basis amount. In 2010, this corresponded to SEK 383,250 or approximately USD 55,000. In addition, a means-tested benefit provides a minimum pension.[7]

The focus of this paper is the activity and performance of individual investors in the PPS (the fully funded participant-directed accounts), not the pension system as a whole. The PPS 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 under management. The Swedish Pensions Agency administers the system, but it is up to individual participants to select how to invest their personal funds.

[7] The pension rights in the notional defined contribution plan are notional in the sense of being linked to the Swedish income index, with a balancing mechanism designed to maintain the financial stability of the system. See Sundén (2006) for a discussion of the overall Swedish pension reforms of the 1990s. For studies of the PPS, see also Cronqvist and Thaler (2004) and Palme, Sundén, and Söderlind (2007).

The system is sometimes referred to as the PPM system, after the acronym of the previous agency handling the system.

The individual accounts of the PPS may represent a small portion of investors' total savings. However, the amounts involved are not insignificant, and they may be highly relevant for individuals who are less likely to participate in the stock market or invest in mutual funds on their own. For example, Dahlquist, Setty, and Vestman (2013) report that a typical individual's savings in the premium pension system corresponds to 2/3 of his or her financial savings outside of the pension system. A back-of-the-envelope calculation (supported by estimates from the agency) indicates that as much as 40% of an individual's pension at retirement can be expected to come from the premium pension. This is partly because much of the funds invested in the PPS are expected to grow at an equity rate, whereas the other pension components are expected to grow at a bond interest rate.

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, 456 funds were registered in the system, and by 2010 there were around 780 funds to choose from. During the period we study there have been 1,230 funds offered. Most of these funds (934 funds), are equity funds, about half of which invest primarily in international equities. The rest are fixed income funds (197 funds), investing mostly in Swedish bonds, and balanced funds (99 funds), investing in equity and fixed income securities. 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 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 historical rate of return and risk (measured over several horizons), the fee, and the fund 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 the agency, which passes this rebate on to the individuals. As a result, the typical effective fee in the pension system is lower than in the retail market. 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. In 2010, this fee amounted to 0.16% of the assets in the system. Hence, the average total fee paid by pension investors was 0.53% of assets for active investors and 0.31% for those in the default fund.

3 Data and benchmarks

We obtained data from the Swedish Pensions Agency on more than six million individual investors and all offered investment options (mutual funds) in the Premium Pension System (PPS). For each individual in the system we observe their initial fund choices and all their fund changes on a daily basis. We also have data on individuals' gender, age, and pension rights in year 2000, a function of individuals' pensionable income that we use as an income proxy. From this population we randomly draw 100,000 individuals. Out of these, we consider 70,755 individuals who were in the system when it was launched in September 2000 and stayed in it until the end of our sample period in May 2010. This sample selection procedure avoids complex issues of how a changing sample composition could affect the results. It does not generate endogeneity problems as the only ways out of the sample are to retire at the statutory age, become disabled or die.

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) was obtained from the agency.

With this data we re-construct individuals' portfolios, day by day, and compute portfolio returns. We compute risk-adjusted performance measures (alphas) by using three different risk-adjustment models that capture mutual funds' investments in local bonds, and local and global stocks. A three-factor model that includes 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) as factors. In this model we compute excess returns by subtracting a proxy for the risk-free rate (JP Morgan's one-month cash rate for Sweden) from the benchmarks. A five-factor model that extends the three-factor model with two benchmarks factors that capture world value/growth and size in the spirit of Fama and French (1993). The value/growth factor is the difference in returns between global value stocks and global growth stocks computed using MSCI world investable indices (value and growth). The size factor is the difference in returns between global small cap stocks and global large cap stocks computed using MSCI world indices. We also consider a six-factor model built by expanding the five-factor model with the inclusion of a world momentum factor. We build the world momentum factor from country indexes, treating each country index in the MSCI all country world universe as an asset and creating a momentum factor across countries as in Asness, Liew, and Stevens (1997) (see also Asness, Moskowitz and Pedersen, 2013). The data used to construct all six factors is obtained from Datastream.

Since the mid-2000s an industry of mass-market financial advisors has emerged. These financial advisors offer a non-individualized service characterized by little human contact that induces a high degree of coordination among their customers' fund changes. We use this fact to classify accounts as directed by individuals (non-coordinated investors) or financial advisors (coordinated investors).[8] We do that by applying 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 at least once made exactly the same fund change (same fund(s) origin and destination and same change date) as a thousand or more other individuals. Second, the individual has done, for at least one fifth of the fund changes, exactly the same change as ten or more other individuals. Using this approach we find 8,115 coordinated investors and 62,640 non-coordinated investors in our sample of 70,755 individuals.[9] Alternative classification algorithms produce similar results, reflecting the fact that in most cases coordination is either extreme or very mild or non-existent.

In this study we are particularly interested in individuals' account activity which we measure using the number of fund changes they make (excluding changes carried out by the PPS when a fund is discontinued or replaced by another). Table I presents the numbers and percentages of individuals in the various investor activity categories, both in our sample and the population. 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

[8] Although we cannot entirely rule out that some non-coordinated individuals may be receiving financial advice for their Premium Pension decisions we believe most of them do not. More personalized advisors, whose activities do not result in coordinated flows, are probably not an economical option for most, if not all, investors in the PPS.

[9] Conversations 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 delivers estimates of the number of individuals on an advisory relation similar to those independently reported by the authority.

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.

We document strong evidence of inertia in fund choices.[10] Approximately 69% of the non-coordinated individuals in our sample made no fund changes during the 2000–2010 period: 30.2% stayed in the default fund for the entire sample period, and 39.0% were initially active and chose one or several funds but have not made a fund change since. In the active investor categories, 16.0% made one fund change; 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 for this group of investors. 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.

Coordinated investors on the other hand are much more active than non-coordinated investors. For example, 31.4% of coordinated investors made more than 20 changes, whereas only 1.2% of non-coordinated investors were equally active. Coordinated investors represent

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

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).

4 Methodology and Results

Individuals who would like to actively manage their portfolios can do that on their own or, less frequently, they can hire a financial advisor to do that for them. These two forms of activity, direct and by proxy, will result in fund changes being made to portfolios, but their implications are clearly different. For this reason in what follows we analyze (non-coordinated) individual investors and (coordinated) advised investors/financial advisors, and their fund changes, separately. This identification is not arbitrary. Our 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.

4.1 Results on non-coordinated investors

Non-coordinated investors are investors who choose and change funds themselves and most likely do not resort to financial advisors. In this section we evaluate the investment performance of non-coordinated investors and relate it to their activity. We also establish causality, from activity to performance, and shed light on the types of fund changes that drive performance for these investors.

4.1.1 Investor activity and performance

We first characterize the relationship between activity, measured by the number of fund changes, and performance. To do that we sort investors into J non-overlapping categories based on the number of fund changes they made during our sample period (1 change, 2–5 changes, etc.). We then estimate the following SURE system with OLS:

$$\bar{r}_{jt} = \alpha_j + \beta_j' f_t + u_{jt}, \text{ for } j = 1, \ldots, J, \tag{1}$$

where $\bar{r}_{jt}$ is the cross-sectional average of the excess returns for category j in day t and 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 is different from another category's alpha, using a Newey and West (1987) estimator of the covariance matrix of the full system.

Table II reports the annualized performance of those portfolios. Returns and alphas are annualized by multiplying them by 252 (the average number of trading days in a year), whereas daily average standard deviations (computed at the individual level) are annualized by multiplying them by the square root of 252. 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 higher Sharpe ratios (not tabulated). 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 higher for more active investors. The same is true of five- and six-factor model alphas obtained using world value/growth and size factors (five-factor model) and also a world momentum factor built from country equity indexes (six-factor model) in addition to the factors in the three-factor model. For instance, individuals in the most active category have an annualized five-factor alpha that is, on average, 7.0% higher than individuals in the passive category outside the default fund (the difference is 7.1% using three-factor alphas or 6.1% using six-factor alphas). 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.

Table II also presents the performance of two categories of passive investors: those who made an active fund choice when entering the pension system in year 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 a five-factor alpha that is 0.47% higher per year than that of passive investors who made an initial choice, although the difference is not statistically significant at usual levels.

These results are further illustrated using box plots of five-factor 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 II 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.

Given that investor activity varies with gender, age and income we further characterize the data by showing how the activity-performance relationship changes when controlling for these variables. For this purpose we use the Hoechle, Schmid, and Zimmermann (2012) 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). As discussed in the Appendix, the panel data approach is a natural extension of the portfolio approach better suited to deal with multiple (potentially continuous) investor characteristics.

Table III presents these results. Although arranged differently, the results in specification I, where individuals' returns are regressed on a constant, a set of dummies for the activity categories, the five factors included in the five-factor model and interaction terms between factors and characteristics, are identical to those reported in Table II. The most active investor category has a 7.0% higher five-factor alpha than the no change category (captured by the constant). In addition, these results indicate that the performance differences between the passive category and all categories including investors making at least six portfolio changes are statistically significant. Adding control variables (age, gender and an income proxy) does not affect the shape of the relationship between activity and performance. Table III 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 in specifications III and IV indicate that ten additional fund changes are associated with a statistically significant 1.1% higher alpha per year, regardless of age, income or gender.

These results provide strong evidence of a positive relation between activity and performance in the context of a defined contribution pension scheme with no transaction costs. The direction of causality, however, is not self-evident. While it could be the case that changes are instrumental in obtaining higher returns, alternative explanations for this relationship are also possible. In particular, causality could run in the opposite direction with lucky investors who experience higher returns erroneously attributing those returns to skill and remaining very active, whereas investors who obtain poor returns become discouraged and stop making changes.

4.1.2 Causality

To investigate the direction of causality we therefore form a new set of portfolios by sorting investors according to their activity *prior* to the performance evaluation period. Every day we assign investors into one of three activity categories based on the number of portfolio changes they made over the previous year (with an embargo of ten days). We sort based on past activity to make sure that it is not high returns that subsequently lead to a large number of changes, and we skip ten days between the date used to sort investors and the return evaluation period to make sure that there are no price impact effects related to fund changes affecting our results. We then form three different calendar time portfolios by equally weighting individual portfolios in each activity category. The first portfolio, labeled "inactive," includes individuals who made a fund choice before the one year sorting period but did not make a fund change during that period. Because these individuals made a fund choice none of them is invested in the default fund during the sorting or evaluation periods.[11] The second portfolio, labeled "active," includes individuals who made at least one change but were not in the top percentile of activity during the sorting period. The last portfolio, labelled "highly active," includes individuals in the top percentile of activity in the sorting period.

The number of portfolio changes over any one-year period is substantially smaller than the number of portfolio changes over the entire ten-year sample period. As an example, the fraction of individuals making at least one change on any given one-year period is, on average, 6.5%, compared to 31% of the individuals making at least one change during the entire sample period. This means that the inactive (over the previous year) category includes a large fraction of the individuals in the sample (60.7%). The active category includes 5.9% of the individuals in the sample, and the highly active category includes a small number of very active investors (on average, as many individuals as the most active category in the previous classification: 0.6% of the individuals in the sample). Individuals who were invested in the default fund during the sorting period account for the rest of the sample.[12]

Panel A of Table IV presents the average returns and alphas obtained by these three groups of investors. The average return of the portfolio of investors who made no changes

[11]This portfolio is not the same as the no change portfolio of Table II for two reasons: first, some investors who made no changes in the sorting period can still make them in the evaluation period; and second this portfolio includes a year and ten days' less data at the beginning of the sample (we need a full year of data to sort investors prior to the performance evaluation period).

[12]We do not report results for the individuals in the default fund up to any given point in time as their performance is closely matches that of the default fund already reported in Table II.

during the sorting period is 3.88% per year, compared to 6.64% per year for the portfolio of investors who made a few changes, and 12.30% per year for the portfolio of investors who made a high number of changes.[13] Three-, five- and six-factor alphas are also increasing in pre-evaluation period activity. For instance, annualized alphas from the five-factor model go from –0.25% for the inactive portfolio to 8.67% for the highly active portfolio. Differences in alphas between these two portfolios, and the active portfolio, are not only economically but also statistically significant.

The importance of fund changes in explaining the observed differences in performance is highlighted by the results of Panel B in the same table. Panel B of Table IV presents the performance that investors would have obtained if they had not made any changes to their portfolios. We construct these counterfactual portfolios by discarding all active fund changes made by investors.[14] Performance is poorer when fund changes are discarded. For instance, we estimate a five-factor alpha of 1.90% per year for individuals in the active category. This alpha decreases to -0.02% per year when no fund changes are kept (this is the alpha that these investors would have obtained if they kept their initial fund allocation). The drop in portfolio performance once we exclude active fund changes is even more significant for individuals in the highly active category, from 7.20% per year to 0.60% per year. Even when excluding all active fund changes the most active investors would have outperformed the least active investors by a statistically significant 0.98% per year, suggesting that individuals in the most active categories made better initial fund choices. However, this outperformance is much smaller than the 7.46% difference per year in actual five-factor alphas between these two groups of investors. These results suggest that while active investors are likely to be more capable investors to start with most of their outperformance of inactive investors is

[13]Due to the requirements of the sorting strategy these portfolios exclude the first year of our sample period. As a result, average returns in Table IV may differ from those reported in Table II.

[14]In 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.

achieved through their ability to actively and profitably change funds (i.e., account activity positively contributes to their results).

To investigate the impact of fund changes on performance further, we next look at the time profile of the contribution of portfolio changes to the observed results. For this purpose we form two different sets of portfolios. The "chosen" portfolios follow the performance of the portfolios selected by each individual investor who makes a portfolio change for either one week, one month, six months, one month ignoring the first week, or six months ignoring the first month. The "discarded" portfolios follow the performance of the portfolios left by each individual during similarly defined periods. We form these portfolios by arranging in calendar time the portfolios chosen and discarded by each individual in our sample, and tracking their returns from the day of the portfolio change and over the specified periods. Mean returns and alphas are then computed on the daily returns of equal-weighted portfolios of individual portfolios included in each category.[15]

The first column of Table V presents the average returns. The remaining columns present three-, five-, and six-factor alphas for each of these portfolios. The chosen portfolios outperform the discarded portfolios over all the horizons we study, and other than in the five-month period starting a full month after the portfolio change, they do so significantly. For instance, the chosen portfolio returns exceed the discarded portfolio returns by an annualized 4.86% in the week following the portfolio change; and by an annualized 4.79% in the month following that change. The difference in five-factor alphas are 4.33% and 4.03% per year for these two portfolios. The differences are still large six months after the portfolio change, although they are no longer statistically significant if we exclude the first month after the change (i.e., when looking at the performance between days +31 and +180 of the portfolio change).

These results reveal that the bulk of the benefits from a portfolio change are obtained in the first month after the change; a period that roughly coincides with the average holding

[15] These portfolios are similar to transaction-based calendar portfolios used by Seasholes and Zhu (2010).

period of the most active investors in our sample (those making more than 50 fund changes over the entire sample period).[16] After that the outperformance of the chosen portfolio weakens, but it is not reversed. The outperformance of the chosen portfolio is not, however, just a matter of a few days, and cannot therefore be attributed to these investors being able to trade at stale prices.[17] There is actually almost no difference between the performance of chosen portfolios in the first week after the portfolio change (mean return 12.86%, five-factor alpha 7.78%) and their performance in weeks two to four (mean return 12.06%, five-factor alpha 6.88%).

By looking at the performance of the portfolios chosen and discarded by individual investors we can confirm that fund changes are instrumental in the higher performance of active investors. It is not just that active investors make better choices to start with and that their account activity has no significant impact on performance. Active investors seem *smart* in the sense of being able to choose funds that outperform during their holding period.

4.1.3 Portfolio change type and performance

The fact that a significant part of the abnormal returns obtained following a portfolio change seem to be confined to a relatively short period of time after the change could indicate that active investors are exploiting the sort of short-term persistence in fund performance identified by Bollen and Busse (2004) (see also Mamaysky, Spiegel and Zhang, 2008, and Lou, 2012). To explore this possibility, and gain a better understanding of how changes help obtain superior performance, we next look at the performance of "chosen" and "discarded" portfolios *prior* to the portfolio change date. We also form counterfactual portfolios that

[16] Not only the chosen portfolios but also the discarded ones exhibit positive abnormal returns over the periods we study them. This is not unreasonable. Most portfolio changes are done by very active investors. A discarded portfolio is then a portfolio that was a chosen portfolio only a short time before. It should not come as a surprise that the discarded portfolio performs similarly to how the chosen portfolio performs between one month and six months after the portfolio choice (reported in Panel E of Table V).

[17] According to our conversations with officers at the Swedish Pension agency, fund changes are executed two days after they are requested by investors, making late trading virtually impossible. Our results confirm that assertion.

alternatively exclude momentum and contrarian changes or fund-selection and market-timing changes. The first of these tests is aimed to examine whether active investors are chasing past fund performance. The latter, to see whether they especially benefit from doing so, and whether changes within an asset class are more or less relevant than changes across asset classes.

We track the returns of the chosen and discarded portfolios during the one-month, one-quarter, one-semester and one-year periods ending the day before the portfolio change date and show the results of this exercise in Table VI. The chosen portfolios outperform the discarded portfolios by a significant margin in all the periods preceding the portfolio change date we study. The difference between the returns, and alphas, of these two portfolios is always significant on the horizons we study and larger the closer we are to the change date. For instance, the annualized difference between the returns of the chosen portfolio and discarded portfolio is 24.18% in the month prior to the change, compared to a still significant 5.14% in the year prior to the change.

Table VII, which shows the percentage of changes for which the chosen portfolio returns are larger than the discarded portfolio returns in the month, quarter, semester or year prior to the portfolio change, describes a similar picture. For instance, if we look at the semester prior to the portfolio change we find that 80.3% of the changes made by relatively inactive investors were to portfolios of funds that outperformed their discarded funds over this period. The same holds true for changes executed by active and highly active investors, 70.4% and 59.0% respectively of their portfolio changes resulted in the selection of a new portfolio of funds with better past performance than the discarded funds.

Together the results in Tables VI and VII suggest that investors are disproportionately going for past winners when making portfolio changes. This is true of very active as well as relatively inactive investors. The results in Table VII also indicate that investors do this in ways that reflect their different holding periods. While relatively inactive investors switched to portfolios of funds with better previous year performance 82.5% of the time, their share of changes to portfolios of funds with better previous month performance was smaller, at 70.6%. In contrast, highly active investors switched to portfolios of funds with better previous year performance only 55.1% of the time, but their share of changes to portfolios of funds with better previous month performance was significantly higher, at 78.1%.

We study whether investors especially benefit from their changes towards funds with better recent past performance by constructing counterfactual portfolios that exclude these changes. We label these changes momentum changes. Specifically, we define a momentum change as a change in which the new fund or set of funds outperformed the old fund or set of funds in the previous six-month period.[18] Similarly, we study whether investors benefit from contrarian changes by constructing counterfactual returns where all changes to a set of funds that underperformed in the previous six-month period are discarded.[19] Panel A of Table VIII presents the results. When momentum changes are excluded, performance decreases for all active categories (even when controlling for traditional momentum factors). In absolute terms, the difference in alphas is 1.49% for the active category and 3.68% for the more active investor category. The difference in alphas with and without contrarian changes on the other hand is small and never significant. Thus, 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.

We next investigate whether changes across asset classes (market-timing) have a more or less relevant contribution to performance than changes within an asset class (fund-selection). 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

[18] Similar results obtain if we use alternative measurement periods. These results are available upon request.

[19] Note that momentum and contrarian changes do not add up to 100%, as we only classify active changes for which we have enough return history to make the comparison.

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.[20] As shown in Panel B of Table VIII, market-timing changes seem to have little effect on performance. The difference in five-factor 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, which are more common than market-timing changes, appear to have a more noticeable impact on performance for active investors.

Overall, these results, together with the results of the previous subsection, suggest that active investors (consciously or unconsciously) tend to pursue strategies that take advantage of short term persistence in fund performance. Importantly, they do this in a context where these strategies seem most economical. As Bollen and Busse (2004) note, short-term persistence would allow an astute investor to predict future performance based on past results and potentially profit from it. Bollen and Busse (2004), however, are adamant that in most cases transaction costs and taxes would eat up the benefits of such strategies. The PPS, by freeing investors from these costs, allows them to substantially profit from these opportunities.

Our analysis of individual level accounts also indicate that active investors in the system are, on average, "smart" in the sense of generally being able to choose funds that outperform during their holding period. This could be because they manage to select skillful managers as argued by the smart money literature (Gruber, 1996, and Zheng, 1999) or because they are able to take advantage of flow-induced price pressure in stocks and funds (Lou, 2012). In any case, it is important to notice that they are able to do this because of the lack of transaction costs in this system.

[20] Note that market-timing and fund-selection changes do not add up to 100%, as we only consider pure market-timing or fund-selection changes, and not changes that are combinations of these two (i.e., changes to other funds some of them in the same asset class some not).

4.2 Coordinated investors

Individuals can choose and change their portfolio on their own or they can hire a financial advisor to help them do that. In what follows we explore the possibility that individual investors may hire an advisor to actively manage their accounts, and their results when doing so. As already explained we identify financial advisors by the type of changes individuals do. We attribute coordinated changes to financial advisors who give recommendations and manage portfolios on a discretionary basis. This identification is not arbitrary. Internal analysis conducted by the Swedish Pensions Agency and casual observations suggest that there is a strong link between coordinated fund changes and financial advisors.

To study the performance of coordinated investors we construct a portfolio that includes all coordinated investors in our sample. The first line of Table IX shows the performance of this portfolio (gross of financial advisors fees). This portfolio has an average return of 1.62% per year and an alpha from the five-factor model of -0.63% per year, similar to the aggregate performance of relatively inactive non-coordinated investors (reported in Table II). Since it is unlikely that coordinated individuals employed a financial advisor during the entire sample period we also construct a portfolio where individuals are included only during the time period we classify them as coordinated. We define the coordinated period as running from the portfolio change immediately before the first multiple change shared by at least 250 individuals until three months after the last multiple change (equally defined) executed by the investor or the end of the sample, whatever comes first.[21] This portfolio has an average return, before any financial advisor fees, of 2.61% per year and an alpha from the five-factor model of 1.07% per year. The aggregate performance of coordinated investors is therefore better when measured during their coordinated period, but differences in average returns and alphas between this portfolio and that of inactive investors, although positive, are not

[21]The first of these conditions intends to capture the move from the individually chosen portfolio to the advisors preferred portfolio. The latter puts a horizon beyond which we assume individuals have stopped using the advisor if there are no further coordinated changes.

statistically significant.

Financial advisors, however, charge a fee for their advice. This fee is not deducted from the investors' returns but paid outside the pension system. The fee typically amounts to between 1% to 2% of assets under management per year, which would significantly lower the actual performance. Table IX shows results for a hypothetical fee of 1.5% of assets under management. Under such fees individuals who resort to financial advisor seem to do as well, during the period the advisory relationship is assumed to run, as relatively inactive individuals do on an after fee basis (see Table II).

Overall, our findings suggest that individuals who resort to financial advisors do not perform better than those who manage their retirement accounts themselves or who are assigned to the default fund. They do not perform significantly worse either. In that sense our results for financial advisors are not as bleak as the picture painted by the nascent literature on this topic (see Bhattacharya, Hackethal, Kaesler, Loos, and Meyer (2012), Hackethal, Haliassos, and Jappelli (2012) and Mullainathan, Nöth, and Schoar (2012) for instance). To some extent this may be because the absence of transaction costs in the pension context favors advisors and active investors in general.

5 The dark side of activity

When investing on personal account investors that buy or sell shares in individual stocks have to pay brokerage fees and absorb bid-ask spreads and the price impact of their trades. That is, investors who trade, not others, pay their entry and exit costs. As Chordia (1996) notes, this is not the case when they invest through mutual funds. Mutual funds, like the ones considered in this study, are required by law to pay a pro-rata share of the net asset value of the fund to each redeeming investor. Due to this, investors who redeem their mutual fund shares are likely to impose externalities on those that do not. These externalities arise because the liquidation of securities results in expenses (brokerage fees, bid-ask spreads, and price impact of trading) that compromise fund performance. These expenses are paid by the fund, not the investor who triggered them, and as suggested in previous studies (e.g. Edelen, 1999; Greene and Hodges, 2002; Karceski, Levingston and O'Neal, 2004; Coval and Stafford, 2007) their impact on performance could be substantial.

To assess whether pension investors flows affect fund performance, we run regressions of a fund's abnormal return on its lagged abnormal returns and various measures of flows:

$$\mathrm{ar}_{pt} = \alpha_p + \sum_{k=1}^{3} \beta_k \mathrm{ar}_{pt-k} + \gamma \mathrm{Outflow}_{pt} + \delta \mathrm{Inflow}_{pt} + \epsilon_{pt}, \tag{2}$$

where ar_{pt} is the daily abnormal return of fund p on day t, $\mathrm{Outflow}_{pt}$ is a measure of the fund's relative outflow generated by the entire population of pension investors (more than six million individuals) and Inflow_{pt} of the relative inflow from pension investors. Relative outflows (inflows) are expressed as a fraction of average outflows (inflows) for each particular fund. We use average flows as a proxy of a fund's capacity to handle outflows and inflows. The daily abnormal return is defined as the sum of the intercept and the residual in our five-factor model regression.

The abnormal return and flows 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.[22] This means that even if the flow 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-flow relationship (similar to Chen, Goldstein, and Jiang, 2010). To account for the cross-sectional correlations in the error terms we use the spatial estimator by Driscoll and Kraay (1998) for the panel.

[22]This is because the Swedish Pension Agency executes fund changes two days after they are requested by investors.

Table X presents the results for equity funds over the 2000 to 2010 period (we find very little price effect on the relatively more liquid bond funds). The focus of our discussion is the coefficient of the flow measures. Specifications I–IV use two dummy variables, one for outflows and one for inflows, to capture whether relative outflows and inflows are larger than certain thresholds on a given day. In specification II, for instance, the outflow (inflow) dummy variable assumes a value of one if outflows (inflows) are ten times larger than the average outflows (inflows) of the fund over the time series. Such extreme flows happen in 1.24% (1.82%) of the observations (indicated in the lower panel), that is, roughly on one day out of 80 (55) trading days for each fund. The effect of an outflow (inflow) of this size is an abnormal return of –6.5 (1) basis points. The results become stronger as we consider more extreme flows. The point estimates in specification IV indicate that outflows (inflows) that are thirty times larger than the average outflow (inflow) of the fund, something that happens in only 0.28% (0.44%) of the fund-days, lead to abnormal returns of –10 (–3) basis points. In all these specifications the coefficients for outflows are strongly significant, while the coefficient for inflows are not.

Interestingly, it is common for extreme flows to cluster and occur two or more days in a row. For instance, for specification IV, 0.05% of the days belong to two-day clusters with extreme outflows, which doubles the economic effect from –10 to –20 basis points. There are also three-day and four-day clusters on 0.02% and 0.01% of days, almost tripling and quadrupling the economic effect.

The asymmetries we observe in the impact of inflows and outflows on NAVs likely reflect the asymmetries that mutual funds face in how they can respond to them. A mutual fund with a large inflow can allocate new money in ways to minimize the price impact of their trades. It can even allocate it to cash, thus also limiting direct trading costs. Often, the fund can mitigate a potential cash drag by taking a long position in index futures (to at least gain some market exposure). A mutual fund with an outflow does not have the same opportunity.

It can use its cash to some extent, but for a large outflow it needs to liquidate parts of its risky assets. The investment statutes typically do not allow a short futures position. As a result, flows are usually more costly when they necessitate sales rather than purchases (see Christoffersen, Keim and Musto, 2008).

These results provide evidence that frequent fund changes induce costs that are borne by the system as a whole, in addition to other costs that investors internalize (e.g. their time or the fee they pay to financial advisors). Extreme outflows force funds to trade, frequently at unfavorable prices. Yet, while flows and in particular redemptions generate transaction costs and fire sales that affect valuations the investors that trigger them bear only a small part of those costs. The same happens with the administrative costs that result from fund changes.[23] All these costs are imposed by a small fraction of investors but borne by the system as a whole, and shared equally by all investors (active or not), generating a potentially significant wealth transfer (see Johnson, 2004).

Financial advisors likely exacerbate this problem by making fund changes less individually costly, and therefore more frequent, and by contributing to the coordination of those changes. As shown in Table X, more than 90% of the investors behind the largest fund outflows/inflows episodes in our sample (those that result in flows that are at least thirty times larger average fund flows) are coordinated investors.

6 Concluding remarks

Investor inactivity in self-directed defined contribution plans is frequently a source of concern for Pension authorities. This concern has at times prompted pension designers to adopt

[23] A 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.

measures to encourage individuals to become more active. Our study suggest that while activity benefits some individual investors, the fund flows generated by this activity affect mutual 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 inactive investors. For example, the most active investors earn approximately 7% higher average returns than inactive investors. As the difference in risk-adjusted returns is of a similar magnitude, the results are not due to risk compensation. Our analysis suggest that part of the outperformance of active investors is due to these investors exploiting the kind of short term persistence in fund returns identified by Bollen and Busse (2004), in a context where the relative absence of transaction costs makes it economical to do so.

The high activity of a minority of individuals, however, seems to burden the pension system. There are several costs (e.g., administrative, trading, and liquidity provision) associated with executing fund changes in the system, yet active investors do not have to pay them. Financial advisors by contributing to coordinate investments and redemptions exacerbate these costs. We argue that measures designed to facilitate and even encourage activity are not always beneficial. In fact, these measures may negatively impact the performance of inherently passive investors.

Our results relate to important pension design issues: How much freedom should individual investors have to choose and change funds? Should fees be charged that either discouraged costly short-term investments or compensated the fund for its transaction costs?[24] Should financial advisors and account managers be restricted in their operations? We address some of these issues in our study, but others should be the subject of future research.

[24] In the US for instance, the SEC encourages redemption fees, particularly for short-term holding periods, but this is not the case in the Swedish premium pension system (see Greene, Hodges and Rakowski, 2007).

Appendix: Estimation methods

The portfolio approach used extensively in the paper 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, traditionally done by way of double- or multiple-sortings, becomes an issue.

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

$$r_{it} = (\alpha + \alpha_z' z_i) + (\beta + \beta_z' z_i)' f_t + \varepsilon_{it}, \tag{3}$$

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 (3) is then:

$$r_{it} = \begin{cases} \alpha + \beta' f_t + \varepsilon_{it} & \text{for } i \in \text{category 1} \\ (\alpha + \alpha_z) + (\beta + \beta_z)' f_t + \varepsilon_{it} & \text{for } i \in \text{category 2.} \end{cases} \tag{4}$$

This is the same as the calendar time approach, since it effectively estimates a separate regression for each of the two categories. This can easily be extended to cases of many categories/dummy variables.

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 (2012) show that the point estimates of α_z in regression (3), which measure how performance depends on 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, we estimate a factor model for each investor, $r_{it} = \alpha_i + \beta_i' f_t + \varepsilon_{it}$. Second, we 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 (2012) 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. The results, and a detailed description, of this experiment are available upon request.

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Table I: Investor activity in the population and sample

	A. All investors				**B.** Non-coordinated investors				**C.** Coordinated investors			
	Population		Sample		Population		Sample		Population		Sample	
	N	%	N	%	N	%	N	%	N	%	N	%
Default fund	1,161,525	26.9	18,947	26.8	1,161,525	30.3	18,947	30.2				
No change	1,483,607	34.3	24,433	34.5	1,483,607	38.7	24,433	39.0				
1 change	612,587	14.2	10,006	14.1	612,587	16.0	10,006	16.0				
2–5 changes	443,096	10.2	7,148	10.1	356,601	9.3	5,737	9.2	86,495	17.7	1,411	17.4
6–20 changes	395,170	9.1	6,415	9.1	161,083	4.1	2,579	4.1	234,087	47.9	3,836	47.3
21–50 changes	200,138	4.6	3,364	4.8	46,880	1.2	734	1.2	153,258	31.4	2,630	31.4
51– changes	28,168	0.7	442	0.6	13,364	0.3	204	0.3	14,804	3.0	238	3.0
All	4,324,291	100.0	70,755	100.0	3,835,647	100.0	62,640	100.0	488,644	100.0	8,115	100.0

The table presents the activity 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. In Panel A all investors are considered; in Panel B non-coordinated investors are considered; in Panel C coordinated investors are considered. The algorithm for determining whether an individual has made coordinated fund changes, or not, is described in the text. All investors have been in the sample over the entire period. The first column in each panel presents the number of investors in the population; the second column presents the percentage of individuals in the population; the third column presents the number of investors in the sample; the fourth column the percentage of individuals in the sample.

Table II: Investor activity and performance—non-coordinated investors

	Mean (% per year)	Standard deviation (% per year)	Alpha-3F (% per year)	Alpha-5F (% per year)	Alpha-6F (% per year)
Default fund	1.75	15.59	−0.42	−0.56	−0.60
	(5.29)		(2.21)	(2.23)	(2.24)
No change	1.73	17.12	−0.83	−1.03	−1.06
	(5.38)		(1.92)	(1.87)	(1.88)
1 change	1.74	17.33	−0.71	−0.85	−0.87
	(5.42)		(1.97)	(1.92)	(1.93)
2– 5 changes	2.49	18.19	0.13	−0.10	−0.31
	(5.54)		(2.23)	(2.37)	(2.21)
6–20 changes	4.09	18.71	1.85	1.65	1.02
	(5.53)		(2.64)	(2.53)	(2.55)
21–50 changes	5.81	18.27	3.44	3.20	2.30
	(5.23)		(2.91)	(2.78)	(2.73)
51– changes	8.62*	18.29	6.29*	5.93*	5.06*
	(5.13)		(3.22)	(3.09)	(3.04)
t-test [p-value]	[0.01]**		[< 0.01]***	[< 0.01]***	[0.01]**
MR-test [p-value]	[0.11]		[0.08]*	[0.06]*	[0.06]*

The table presents the performance of individuals categorized according to the number of fund changes they have made. See Table I for the categories. The first two columns present the mean and standard deviation of returns obtained by individuals in each category. The remaining columns present three different alpha measures for each category. Alpha-3F 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; Alpha-5F refers to the alpha in a five-factor model with world value/growth and size factors in addition to the factors in the three-factor model; Alpha-6F refers to the alpha in a six-factor model with a world momentum factor in addition to the factors in the five-factor model. See the text for details. The statistics are computed on daily returns of individuals' portfolios during the sample period. The mean, standard deviation, and alphas are expressed in % per year. 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 III: Investor activity, performance, and characteristics

	I	II	III	IV
Constant (no change)	−1.028 (1.877)	−1.456 (2.192)	−0.838 (1.899)	−1.325 (2.193)
1 change	0.182 (0.425)	0.197 (0.423)		
2– 5 changes	0.933 (0.915)	0.945 (0.909)		
6–20 changes	2.676* (1.592)	2.675* (1.588)		
21–50 changes	4.230** (2.046)	4.199** (2.040)		
51– changes	6.957*** (2.458)	6.999*** (2.453)		
Number of changes			0.111** (0.047)	0.111** (0.047)
Age		0.007 (0.008)		0.007 (0.008)
Gender		0.273*** (0.098)		0.275*** (0.098)
Income		−0.017 (0.024)		−0.001 (0.030)
R-squared	0.553	0.553	0.552	0.553

The table presents the results of pooled regressions of non-coordinated individuals' daily excess returns on factors, measures of the number of fund changes by each investor and other individual characteristics. The factors are the excess returns of the Swedish stock market, the Swedish bond market, the world stock market, a world value/growth factor, and a world size factor (see the text for details). The coefficients on these factors are allowed to vary across the individuals' characteristics. For brevity, the coefficients on the factors and results on default fund investors are not presented in the table. The number of fund changes is measured using either a dummy variable for each activity category (see Table I) or a variable counting the number of fund changes. Other characteristics are the individuals' age in year 2000, gender (one if man, and otherwise zero) and pension rights in year 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 IV: Investor activity prior to the evaluation period and performance

	Mean (% per year)	Alpha-3F (% per year)	Alpha-5F (% per year)	Alpha-6F (% per year)
A. Actual Performance				
Inactive	3.88	−0.25	−0.26	−0.52
	(5.46)	(1.90)	(1.84)	(1.87)
Active	6.64	2.53	1.90	0.69
	(5.10)	(2.50)	(2.41)	(2.29)
Highly active	12.30**	8.67**	7.20**	5.39*
	(4.93)	(3.55)	(3.42)	(3.19)
t-test [p-value]	[0.01]**	[< 0.01]***	[0.01]**	[0.03]**
MR-test [p-value]	[0.02]**	[< 0.01]***	[0.03]**	[0.08]*
B. Counterfactural performance (excl. fund changes)				
Inactive	3.67	−0.43	−0.38	−0.65
	[0.30]	[0.35]	[0.55]	[0.64]
Active	3.94	−0.06*	−0.02	−0.37
	[0.11]	[0.09]	[0.20]	[0.45]
Highly active	4.53**	0.57***	0.60**	0.19**
	[0.01]	[< 0.01]	[0.02]	[0.04]
t-test [p-value]	[0.11]	[0.06]*	[0.06]*	[0.10]
MR-test [p-value]	[0.09]*	[0.04]**	[0.04]**	[0.07]*

Panel A of this table shows mean returns and alphas for non-coordinated individuals categorized according to the number of fund changes they made in the one-year period finishing ten days before the return measurement day. The category "inactive" refers to individuals who made a fund choice but did not make a fund change during the sorting period. The category "active" refers to individuals who made at least one change but were not in the top percentile of activity during the sorting period. The category "highly active" refers to individuals in the top percentile of activity in the period. Mean returns and alphas are computed on daily returns of non-coordinated investors' portfolios and expressed in % per year. 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 "inactive" and "highly active." 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. Panel B presents counterfactual alphas, i.e., the alphas these investors would have obtained if they had not made any fund changes during the measurement period. The p-value of a test of the difference between the actual and a counterfactual alpha is reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table V: The performance of chosen and discarded portfolios

	Mean (% per year)	Alpha-3F (% per year)	Alpha-5F (% per year)	Alpha-6F (% per year)
A. One week (1–7)				
Chosen	12.86	9.11	7.78	6.63
Discarded	8.00	4.30	3.45	2.01
Difference	4.86***	4.81***	4.33***	4.61***
t-test [p-value]	[< 0.01]	[< 0.01]	[< 0.01]	[< 0.01]
B. One month (1–30)				
Chosen	12.17	8.44	7.03	5.52
Discarded	7.38	3.77	3.00	1.56
Difference	4.79***	4.67***	4.03***	3.96***
t-test [p-value]	[< 0.01]	[< 0.01]	[< 0.01]	[< 0.01]
C. Six months (1–180)				
Chosen	8.76	4.90	3.92	2.16
Discarded	6.59	2.88	2.39	1.16
Difference	2.17**	2.02**	1.54*	1.01
t-test [p-value]	[0.03]	[0.02]	[0.08]	[0.20]
D. One month, ignoring the first week (8–30)				
Chosen	12.06	8.32	6.88	5.23
Discarded	7.23	3.64	2.90	1.48
Difference	4.83***	4.67***	3.98***	3.75***
t-test [p-value]	[< 0.01]	[< 0.01]	[< 0.01]	[0.01]
E. Six months, ignoring the first month (31–180)				
Chosen	7.98	4.11	3.22	1.42
Discarded	6.41	2.68	2.24	1.06
Difference	1.58	1.42	0.98	0.36
t-test [p-value]	[0.11]	[0.12]	[0.28]	[0.64]

The table presents the average returns and alphas of different transaction-based calendar portfolios. The "chosen" portfolios follow the performance of the portfolios selected by each non-coordinated individual who makes a portfolio change for either one week, one month, six months, one month ignoring the first week or six months ignoring the first month. The "discarded" portfolios follow the performance of the portfolios left by each individual during similarly defined periods. Mean returns and alphas are computed on daily returns of equally weighted investors' portfolios arranged in calendar time during the 2001 to 2010 period, and expressed in % per year. The first column presents the average returns, and the remaining columns present three different alpha measures (see Table II or the text for details) for each of these portfolios. The p-values of a t-test of zero difference, based on standard errors robust to conditional heteroscedasticity and serial correlation up to four lags as in Newey and West (1987), are reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table VI: The performance of the chosen and discarded portfolios prior to the portfolio change date

Holding period	Mean (% per year)	Alpha-3F (% per year)	Alpha-5F (% per year)	Alpha-6F (% per year)
A. One month (–1;–30)				
Chosen	33.92	30.33	29.08	28.14
Discarded	9.74	6.16	5.38	4.20
Difference	24.18***	24.17***	23.70***	23.94***
t-test [p-value]	[< 0.01]	[< 0.01]	[< 0.01]	[< 0.01]
B. One quarter(–1;–90)				
Chosen	29.14	25.38	24.13	23.21
Discarded	15.80	12.21	11.38	10.37
Difference	13.35***	13.17***	12.75***	12.84***
t-test [p-value]	[< 0.01]	[< 0.01]	[< 0.01]	[< 0.01]
C. One semester (–1;–180)				
Chosen	24.67	20.81	19.56	18.70
Discarded	16.33	12.68	11.83	10.89
Difference	8.34***	8.13***	7.73***	7.81***
t-test [p-value]	[< 0.01]	[< 0.01]	[< 0.01]	[< 0.01]
D. One year (–1;–365)				
Chosen	20.28	16.31	15.16	14.19
Discarded	15.14	11.44	10.60	9.85
Difference	5.14***	4.87***	4.56***	4.64***
t-test [p-value]	[< 0.01]	[< 0.01]	[< 0.01]	[< 0.01]

The table presents the average returns and alphas of the "chosen" and "discarded" portfolios prior to the portfolio change date. Average returns and alphas for these portfolios are reported for the one-month, one-quarter, one-semester and one-year periods prior to the change. Mean returns and alphas are computed on daily returns of equally weighted investors' portfolios arranged in calendar time and expressed in % per year. The first column presents the average returns, and the remaining columns present three different alpha measures (see Table II or the text for details) for each of these portfolios. The p-values of a t-test of zero difference, based on standard errors robust to conditional heteroscedasticity and serial correlation up to four lags as in Newey and West (1987), are reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table VII: Performance chasing

Holding period	Previous month	Previous quarter	Previous semester	Previous year
Inactive	70.6	77.6	80.3	82.5
Active	78.8	76.3	70.4	62.9
Highly active	78.1	65.6	59.0	55.1

This table presents the percentage of changes for which the chosen portfolio returns are larger than the discarded portfolio returns in the month, quarter, semester or year prior to the fund change. These figures are based on classified changes (those with available prior return information) and presented for "inactive", "active" and "highly active" individuals as defined in Table IV.

Table VIII: Counterfactual alphas

A. Counterfactual alphas, excluding momentum or contrarian changes

	Alpha	Alpha w/o momentum	Excluded changes (%)	Difference in alphas	Alpha w/o contrarian	Excluded changes (%)	Difference in alphas
Inactive	−0.26	−0.14	66.2	−0.12	−0.02	16.2	−0.23
	(1.84)	(2.02)		[0.53]	(2.03)		[0.62]
Active	1.90	0.41	67.7	1.49	1.89	28.5	0.01
	(2.41)	(1.94)		[0.25]	(2.52)		[0.96]
Highly Active	7.20**	3.52	57.9	3.68**	6.92*	40.2	0.27
	(3.42)	(2.53)		[0.03]	(3.92)		[0.79]

B. Counterfactual alphas, excluding market timing or fund selection changes

	Alpha	Alpha w/o market timing	Excluded changes (%)	Difference in alphas	Alpha w/o fund selection	Excluded changes (%)	Difference in alphas
Inactive	−0.26	0.08	22.2	−0.34	−0.20	49.9	−0.05
	(1.84)	(2.01)		[0.47]	(1.85)		[0.76]
Active	1.90	2.17	24.2	−0.27	0.42	58.4	1.48*
	(2.41)	(2.52)		[0.54]	(1.91)		[0.07]
Highly active	7.20**	6.65*	23.5	0.55	4.89*	57.0	2.31**
	(3.42)	(3.55)		[0.39]	(2.78)		[0.02]

This table presents alphas for individuals categorized according to the number of fund changes they made over the previous year (see Table IV for the categories). Panel A of this table present alphas with all changes (repeated from Table IV) and counterfactual alphas that reflect the alphas these investors would have obtained if they had not made momentum or contrarian changes. Panel B presents alphas with all changes as well as counterfactual alphas that reflect 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 and expressed in % per year. Alpha refers to the intercept in a five-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, the world stock market, world value/growth, and world size 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. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table IX: Investor activity and performance—coordinated investors

	Mean return (% per year)	Standard deviation (% per year)	Alpha-3F (% per year)	Alpha-5F (% per year)	Alpha-6F (% per year)
A. Level					
Coordinated investors (all, gross)	1.62	16.27	−0.65	−0.63	−0.83
	(5.11)		(2.04)	(1.98)	(2.00)
Coordinated period (coordinated period, gross)	2.61	13.40	0.08	1.07	0.88
	(5.01)		(2.19)	(2.09)	(2.11)
Coordinated investors (all, net: 1.5% fee)	0.12	16.27	−2.15	−2.13	−2.33
	(5.11)		(2.04)	(1.98)	(2.00)
Coordinated period (coordinated period, net: 1.5% fee)	1.11	13.40	−1.42	−0.43	−0.62
	(5.01)		(2.19)	(2.09)	(2.11)
B. Difference to "uncoordinated, no change"					
Coordinated investors (all, gross)	−0.10		0.17	0.40	0.22
	[0.90]		[0.81]	[0.56]	[0.74]
Coordinated period (coordinated period, gross)	0.88		0.91	2.10	1.94
	[0.61]		[0.58]	[0.19]	[0.22]
Coordinated investors (all, net: 1.5% fee)	−1.60*		−1.33*	−1.10	−1.28*
	[−0.06]		[−0.08]	[0.11]	[−0.06]
Coordinated period (coordinated period, net: 1.5% fee)	−0.62		−0.59	0.60	0.44
	[0.72]		[0.72]	[0.70]	[0.78]

The table presents the performance of coordinated individuals during the entire sample period and during the coordinated period. Performance is alternatively reported gross or net of a hypothetical financial advisor fee of 1.5% per year. The first two columns present the mean and standard deviation of returns obtained by individuals in each category. The remaining columns present three different alpha measures for each category. Alpha-3F 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; Alpha-5F refers to the alpha in a five-factor model with world value/growth and size factors in addition to the factors in the three-factor model; Alpha-6F refers to the alpha in a six-factor model with a world momentum factor in addition to the factors in the five-factor model. The statistics are computed on daily returns of individuals' portfolios during the sample period. The mean, standard deviation, and alphas are expressed in % per year. Standard errors, robust to conditional heteroscedasticity and serial correlation up to four lags as in Newey and West (1987), are reported in parentheses. The table also reports the difference between coordinated investors means or alphas and those of inactive ("no change") uncoordinated investors. The p-values of these tests are reported in square brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table X: Abnormal returns and flows

	I Dummy for rel. flow > 5	II Dummy for rel. flow > 10	III Dummy for rel. flow > 20	IV Dummy for rel. flow > 30	V Linear regression
Relative outflow	−0.055**	−0.065**	−0.083**	−0.098**	−0.00068***
	(0.022)	(0.030)	(0.038)	(0.043)	(0.00025)
Relative inflow	0.023	0.012	−0.019	−0.027	0.00010
	(0.016)	(0.023)	(0.038)	(0.053)	(0.00037)
R-squared	0.036	0.036	0.036	0.036	0.036
Means of dummy variables (%):					
Outflow dummy	3.32	1.24	0.47	0.28	
Inflow dummy	3.89	1.82	0.75	0.44	
Fraction of flows (on dummy days) due to coordinated investors:					
Outflow	0.78	0.85	0.90	0.93	
Inflow	0.69	0.77	0.85	0.88	

The table presents the results of panel regressions of a mutual fund's daily abnormal return on measures of relative flows. The abnormal return is obtained from the five-factor performance model discussed in the text. The abnormal return is defined as the sum of the intercept in the performance regression and the residual. The relative outflow (inflow) is the fund specific outflow (inflow) on a day divided by the time series average outflow (inflow) of the fund. Specifications I–IV use dummies that capture whether relative outflows (inflows) are larger than certain thresholds on a given day, whereas specification V uses the relative outflows (inflows) as a linear regressor. All specifications include three lags of the abnormal return variable and fund fixed effects (not tabulated). Standard errors, robust to conditional heteroscedasticity and spatial autocorrelations up to four lags as in Driscoll and Kraay (1998), are reported in parentheses. The "means of dummy variables" show the fraction (in %) of the dummy variable observations being equal to one. The "fraction of flows due to coordinated investors" shows the average ratio of coordinated investors' flows (from/to a specific fund) over total flows (from/to the fund) for all days when the dummy variable is equal to one. The sample includes all equity funds over the 2000 to 2010 period. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Figure 1: Investor activity and performance—non-coordinated investors

The figure depicts the median, interquartile range and 95% whiskers of alphas for various investor categories. Alpha refers to the intercept in a five-factor performance model using the excess returns of the Swedish stock market, the Swedish bond market, the world stock market, as well as world value/growth and size (SMB) portfolios 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. Below each category, the fraction of individuals in the category is reported in square brackets. All investors have been in the sample over the entire period.