Mislearning and (Poor) Performance of Individual Investors*

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Abstract

We study individuals' incentives to make investment decisions. Using data from a large pension system we find that individuals who are active in managing their investments have, on average, poor performance. We provide robust evidence suggesting that learning plays an important part in this phenomenon. Indeed, individuals who have made successful investment decisions in the past go on to trade more frequently. However, this result holds when using a naive definition for successful decisions. Also, average performance is negatively related to the number of investment decisions, casting doubt on the existence of market timing skills.

JEL classification: C15; D03; D14; G11.

Key words: Behavioral Finance, Pension Savings, Learning, Investment Performance.

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1 Introduction

The investment decisions made by individuals have received increasing attention in the last years. There are both academic and policy reasons for this. Regarding the former, many times investment decisions seem to differ from what theory predicts. Indeed, theoretical models predict that rational agents should make their portfolio decisions taking into consideration factors such as: their investment horizon (Merton 1969, Campbell and Viceira 2002 and Viceira 2008); human capital and expected volatility of wages (Cocco et al. 2005 and Gomes et al. 2008), and other sources of wealth, such as housing (Browning and Crossley 2001), among others. With respect to the latter, if investment decisions are non-rational or sub-optimal, this could have negative and relevant welfare effects for individuals (Calvet et al. 2007).

We analyse the determinants and performance of investment decisions made by individuals, as well as the degree in which learning from past decisions affects future behaviour. We do this by using a unique data set built from administrative records, which allows us to study the investment decisions made by members of the Chilean defined contribution (DC) pension scheme.[1] Chile constitutes and interesting study case because since 1981, its pension system has a DC scheme as its main pillar. Additionally, members have considerable flexibility in choosing the way in which their savings are invested. This could lead to undesired outcomes, since the vast majority of members of pension schemes display a low level of financial knowledge.[2]

Our paper studies the performance of investment decisions within pension plans. Barber and Odean (2013) provide a comprehensive summary of studies about the performance of individual investors. There is widespread evidence that the average investor obtains poor performance and trades too much (Odean 1999, Barber and Odean 2000, Barber and Odean 2001, Calvet et al. 2007, Chuang and Susmel 2011, Døskeland and Hvide 2011, and Kuo and

[1]Even though DC schemes are not dominant in many developed countries, their presence has increased over time. Currently, there are mandatory DC plans in 10 OECD countries. Moreover, in countries like the US and the UK there are voluntary scheme with DC characteristics.

[2]See, e.g. Moure (2016) for evidence about the level of financial knowledge for the Chilean case, and Lusardi and Mitchell (2008, 2011) for the US.

Lin 2013). For members of pension plans, previous studies report the presence of inertia about investment decisions (Madrian and Shea 2001, Agnew et al. 2003, Mitchell et al. 2006, Bilias et al. 2010 and Tang et al. 2012). When members do trade, they fail to diversify adequately their savings (Tang et al. 2010). Also, evidence shows that there is heterogeneity in the degree of involvement in investment decisions, with higher participation for individuals with higher financial wealth and higher income (Agnew et al. 2003, Engström and Westerberg 2003, Cronqvist and Thaler 2004, Calvet et al. 2009 and Tang et al. 2012). In related work, Kristjanpoller and Olson (2014) use Chilean data and find that younger people, men, people with lower incomes and with low financial knowledge are less likely to make investment decisions. However, this study doesn't focus on the topics of performance and learning incentives.

Our paper is also related to the strand of the literature that studies the existence of learning in financial markets.[3] Previous research shows that past investment performance can predict a higher frequency of future trading decisions (Glaser and Weber 2009, Meyer et al. 2012 and Barber et al. 2014). The rationale behind this is that, by making investment decisions, individuals may learn about their ability to trade. In this line, investors' self-perceived ability has been showed to be relevant in order to start trading (Linnainmaa 2011). Furthermore, it has been showed that investors stop trading if they discover that they lack the skills for this task (Seru et al. 2009). In some cases performance has been showed to improve as individuals gain experience from past trades (Nicolosi et al. 2009 and Meyer et al. 2012).

From a financial stability point of view, understanding the way in which investors learn about their ability is a highly relevant issue. For instance, Mahani and Bernhardt (2007) develop a model where the presence of individuals that learn about their trading ability has general equilibrium effects on bid-ask spreads and liquidity. Empirically, Da et al. (2018) describes the increasing frequency of active investment decisions by members of the Chilean pension system. The authors show that the presence of coordinated investment decisions has

[3]Specifically, we focus on learning related to trading experience. However, see Pastor and Veronesi (2009) for a review of other applications of learning in financial decisions.

generated price pressure and increased volatility in the stock market.

Our work contributes to the existent literature in several ways. First, we shed light on the motivations that lie beneath individuals' investment decisions. Specifically, we show that poor performance is spurred by feed-back effects produced by the use of naive learning rules. To the best of our knowledge, this finding has not been reported before for members of pension plans. Second, regarding performance, we use unique data to provide new evidence regarding the effects of investment decisions in a large pension system. We show that the result about average active investors obtaining poor performance seems to be partially dependent on the period under examination. Third, we find robust evidence that members with a larger (lower) number of investment decisions are more (less) likely to obtain worst (better) performance. These results, along with simulation exercises, suggest that good performance is the result of luck rather than skill.

From a policy stand, our results suggest that the advantages of having flexibility in the way in which pension plan members invest should be weighed against the actual outcomes obtained by members.[4] Moreover, the possible benefits of this flexibility need also be weighted against potential negative effects on financial stability related to the presence of frequent ans possibly coordinated investment decisions. Our results also highlight the need to improve our understanding of the way in which individuals learn about the consequences of their investment decisions.

The rest of the paper is structured as follows. In Section (2) we describe the institutional setup four our data. Section (3) contains our empirical findings regarding performance and learning. Section (4) concludes.

2 Institutional Setup

The Chilean DC system was introduced in 1981. Participation is mandatory for all the civil working force. Coverage of the system reaches 75% of working-age population. The contri-

[4]Ahmed et al. (2018) claims that a similar dilemma exists regarding the freedom to make investment choices in 401(k) plans. Moreover, Stolper (2018) provides evidence suggesting that even well-intended financial advice may fail to improve households' financial decisions.

butions made by members are invested by six Pension Fund Managers (PFMs). Assets under management have reached the considerable size of 70% of GDP. The investment guidelines for pension funds are largely contained in the Regulator's Pension Fund Investment Regime, which establishes detailed quantitative limits per instrument, group of instruments and issuer.

Since the PFMs are in charge of taking investment decisions, members do not choose individual assets. However, since August 2002, both mandatory and voluntary savings have been invested under a multi-fund scheme. This consists of five types of fund (A, B, C, D and E), differentiated mainly by the proportion of their portfolio invested in equity. The maximum investment limits in equities for these funds are 80%, 60%, 40%, 20% and 5%, respectively. Historically, the PFMs have chosen portfolios close to this limit. As of December 2016, equity exposition for funds A-E was: 77.9%, 58.2%, 35.7%, 15.7% and 3.5%, respectively.

Members are free to choose any fund, with the exception of an age-related restriction that keeps older members from choosing fund A. Also, members are allowed to invest their savings combining up to two types of fund. In order to make a fund change, an individual must attend in person to one of his PFM's offices. Alternatively, if he has a web password, it is possible to request the fund change through the PFM's website. PFMs are required to fulfil the request in four business days. Moreover, there is no limit on the maximum number of fund changes. Although they are allowed to, in practice no PFM has applied charges for fund changing requests. However, whenever PFMs make portfolio adjustments, they have to incur in brokerage fees. The fees associated to assets directly bought by PFMs are paid out of their pockets, whereas the ones associated to assets held indirectly (e.g. mutual fund shares) are deducted from the pension funds themselves and amount to approximately 0.3% of AUM.

Notwithstanding the above, if members do not opt for a type of fund, they are assigned to a default allocation, which features a decreasing equity exposure as members age. In our empirical analysis we leave out fund changes associated with the default investment strategy and focus on changes explicitly requested by members.

The performance of the funds in terms of real returns has showed considerable dispersion.[5] Nevertheless, performance among PFMs is similar. During 2007-2016, the correlation of monthly returns for the same type of fund among PFMs averaged 0.95.

3 Empirical Results

3.1 The Data

Since members of the Chilean pension system can choose between five different types of fund, rather than studying direct asset holdings, we will analyse which members make fund changes and the impact of these decisions. The source of information is the Supervisor's Members Data Set (Base de Datos de Afiliados or *BDA*), which contains administrative records of all members in the private pension system. This data has characteristics that make it particularly interesting and well suited for our study. First, while learning has been studied using data from day traders and brokerage accounts, there is less evidence about learning for members of pension plans. Second, the motivations for trading can be varied, including: liquidity needs, tax-loss trading, life-cycle motives and market timing objectives, among others. However, in our case, we can rule out some of these factors (e.g. liquidity needs) and focus on issues such as life-cycle elements and market timing. Finally, we have access to both the exact day in which members changed funds and the pension funds' NAV on that day. This allows us to give a precise figure of the performance obtained by these members. We do face a potential limitation, since we do not have data on other forms of savings. However, we argue that in our case this is not a major issue for two reasons. First, for most Chilean workers, pension accounts are the main type of savings. Indeed, according to the 2009 Social Protection Survey, only 1.1% of members of the DC pension scheme held investments in mutual fund shares, while only 0.8% owned bonds and shares. Second, while more individuals have voluntary pension saving accounts (around 15% of members), most of these savings (63%) are invested with PFMs, which means that they are captured in our

[5] Fund A records an average real annual return of 6.13% between September 2002 and December 2016. Fund B follows with a return of 5.23%. In the same period, Funds C, D and E show an average real annual return of 4.90%, 4.54% and 3.92%, respectively.

data.

We limit our study to non-retired members who were already in the scheme at the beginning of 2007. This allows us to maximize the horizon over which we can evaluate the performance of the investment decisions. We make no distinction regarding changes of funds that occur between PFMs. We justify our methodological choice with three arguments. First, although theory suggests that PFMs' attributes such as fees are relevant to change from one manager to other, previous studies show that members of the Chilean pension scheme have low fee elasticity.[6] Second, as we report above, there is a high degree of correlation between PFMs' portfolios. This suggests that when members decide to switch PFMs, their decision is not motivated by the performance of pension funds. Finally, the number of changes of PFM is relatively low in our sample: less than 10% of fund changes were accompanied by a PFM switch. Nevertheless, we do control for changes between PFM in our regression analysis.

We follow the behaviour of our sample from February 2007 to December 2016. Given that administrative data on fund changes began to be recorded only recently, we cannot explore data prior to 2007. Our sample is consisted of 62,865 individuals, from which 4,157 made at least one voluntary change of fund. The data shows that roughly 18,000 changes were made during this period. Therefore, only 6.6% of our sample made active investment decisions. This inertia is consistent with data for members of 401(k) plans.

Under the current institutional setup, individuals are free to make fund changes for both, their mandatory and voluntary savings accounts. We choose to treat all fund changes in the same way, without making distinctions of whether the change was made in the mandatory or voluntary account. We argue that this choice seems adequate, as it simplifies the analysis and the potential loss of information is minimal.[7] Therefore, we define three types of change

[6] Berstein and Cabrita (2007), Arenas de Mesa et al. (2008) and Mitchell et al. (2008) study the importance of fees and other factors that determine the decision of changing between PFMs.

[7] Indeed, we have roughly 18,000 changes in our sample. From these, 87% are changes in mandatory accounts. A potential drawback from our approach is that we could lose information by not making a distinction between account types. This would be the case, for instance, if there are simultaneous changes in the mandatory and voluntary accounts that result in opposite changes in equity exposure. This is a very rare event in our sample. Considering all changes in voluntary accounts, we only have 714 cases (3.9% of all fund changes) where there are simultaneous adjustments in the mandatory and voluntary accounts. Moreover, only in 20% of these cases (0.8% of total changes in our sample) are there opposite adjustments in equity exposure.

variables: Change, More Risk and Less Risk. The first variable takes the value of 1 in the month during which an individual makes a fund change and 0 otherwise. The second (third) variable takes the value of 1 in a month if the individual increased (decreased) his equity exposure and 0 otherwise.[8]

Table (1) shows the descriptive statistics for our sample, which we have divided in four groups. Group 1 is composed of 58,602 individuals (93.3% of our sample) who have not made any voluntary fund change. We further divide in subgroups the remaining 4,158 individuals (6.7% of our sample) with at least one fund change. Group 2 is formed by 2,353 individuals (3.7% of our sample) with up to three fund changes, which is equivalent to the median number of changes for those with at least one change. Group 3 contains 797 individuals (1.3% of our sample) four to six fund changes (roughly the 75th percentile of fund changes). Finally, Group 4, is formed by 1,003 individuals (1.6% of our sample) with more than six fund changes

Since we are not able to observe individuals from the moment they join the system until they retire, it could be argued that the way in which we divide our sample is questionable. For instance, it could be possible that an individual has made fund changes before the beginning of our sample. In this case we could incorrectly classify him in Group 1 if he temporarily "paused" his investment decisions during our sample period. We will address this concern in our robustness analysis and provide evidence to argue that this limitation does not seem to affect our conclusions.

Age is measured in years. There is not a clear pattern between groups, although Group 4 is slightly younger than the Group with no changes. The next variable is the log of the total balance in pension savings, including both mandatory and voluntary accounts. This variable is monotonically increasing as we move from the 1st to 4th group. Indeed, the average balance is CLP 2.3 million for individuals with no changes and this figure increases up to CLP 12.9 million for the group with the higher number of changes.[9] Next, we have the

[8]We could have alternatively defined a dependent variable that takes three different values for equity exposure increases, decreases or no changes. We opt for a simpler, binary approach in order to have a clearer understanding of the factors motivating fund changes by individuals. Nevertheless, in our robustness analysis we use more complex categorical dependent variable models.

[9]One USD equals approximately 660 CLP.

log of monthly income, measured in Chilean pesos, leaving out months without mandatory contributions. Wages increase as we move across groups and the group with the most changes has salaries well above the rest of groups (CLP 800,000 versus CLP 193,000 for the 1st group). Voluntary pension savings, VPS, is a dummy variable that takes the value of 1 (0) for periods in which individuals made (did not make) voluntary savings. Periods without mandatory contributions, which we define as unemployment, are less frequent in groups with more fund changes. Also, males are more prone to make fund changes. Next, we describe fund changes. For the 2nd group, we register voluntary changes 1.5% of time. This figure rises to 12.1% for the 4th group. In our 10-years sample, the average total number of changes is less than one for the 2nd group and almost four for the last group. Regarding the more risk and less risk variables, the frequency of these events increases as we move from group 2 to 4, while across all groups the predominant change consisted in lowering equity exposure. Equity is the mean equity exposure, constructed as a weighted average of exposure in mandatory and voluntary accounts, expressed in percentage of total savings. Change PFM takes the value of 1 if the individual changed from PFM during that month and 0 otherwise. We consider this variable to control for the fact that fund changes may we motivated by advise received when one individual switches between PFMs. Web Password takes the value of 1 if an individual had obtained the password that is required in order to make fund changes through a PFM's website and 0 otherwise. The main takeaway is that fund changes are made mainly by younger males; individuals with higher income; and higher savings.

TABLE (1) AROUND HERE

Table (2) sheds further light on the frequency and type of fund change made by individuals. We have classified a fund change in the following categories: -4, -3, -2, -1, 0, 1, 2, 3, 4. A negative number is associated to a reduction in equity exposure. The largest adjustment of this type would be a -4, equivalent to moving from fund A to fund E. The lowest adjustment would be -1, which means that the individual change to the next lowest equity fund (e.g. moving from fund A to fund B, or from fund B to fund C and so on). A positive number means an increase in equity exposure, with the largest adjustment being 4 (moving from fund E to fund A). Finally, a value of 0 means no fund change. This table shows that Group 2 made a total of 4,155 fund changes during our sample (this means that there were no fund changes 98.52% of the time). Most of the fund changes in this group correspond to reductions in equity exposure, with 21.83% of total changes being the smallest adjustment (e.g. fund change type -1). It is interesting to note that, as we move to groups 3 and 4, the number of fund changes increases but also large equity adjustments become more frequent. For instance, the most common fund changes in Group 4 were between funds A and E (more than half of total changes were -4 or 4).

TABLE (2) AROUND HERE

Figure (1) shows that historically, fund changes did not occur often. However, the Subprime Crisis seems to have changed this. During 2008 pension funds experienced negative returns for the first time since 2002.[10] A downside of engaging in extreme equity exposure adjustments amid periods of high volatility is the possibility of incurring in heavy loses. This was the case of individuals that changed from high-equity funds, such as Fund A, to low-equity funds, such as Fund E, during the last months of 2008. We can also see that the percentage of fund changes associated to extreme reductions in equity exposure (i.e. changes from Fund A to Fund E) represented 40% of the total number of voluntary fund changes. Moreover, the number of changes has a positive trend. Extreme reductions and increases to equity exposure can account for more than half of total changes.

FIGURE (1) AROUND HERE

3.2 Performance

We evaluate the performance achieved by individuals making at least one voluntary fund change during the 2007 to 2016 period. We measure performance in two ways. First, we estimate the raw annual (geometric) average return obtained by those individuals with one or

[10]Previously, the minimum return experienced had been -2.52% (fund C) in 1995. Fund A closed 2008 with a staggering loss of -40%. During 2009 the same Fund earned a 43% return. Nevertheless, this fund did not regain its pre-crisis NAV until 2014.

more fund changes. Second, since differences in raw returns could be associated to variations in the risk that individuals are taking (e.g. a low return strategy could be associated to low volatility), we also estimate Jensen's Alpha, which takes into account the risk present in each particular investment strategy.[11]

Our data includes information regarding the exact day in which each fund change took place and we also know the daily funds' NAV. Returns are measured in real terms. We use this input to estimate the raw and abnormal returns earned by investors. For the latter, we follow Meyer et al. (2012), Kosowski et al. (2006) and Carhart (1997) and use a single factor model, since this type of models' results are not significantly different from those produced by multi-factor models. For each individual we run the following regression:

$$R_{i,t} - R_{f,t} = \alpha + \beta \left(R_{m,t} - R_{f,t} \right) + u_t \tag{1}$$

where $R_{i,t}$ is the real return obtained by individual i in month t; R_f is a short-term inflation-adjusted interest rate for the Chilean market; $R_{m,t}$ is the real return obtained by the Chilean stock index;[12] and u_t is a possibly auto-correlated disturbance.

Panel (a) in Table (3) shows the performance of each pension fund. Fund A was the most volatile and worst-performing fund, both in terms of raw and abnormal returns. As we will discuss in our robustness analysis, the losses during the Sub-prime Crisis contribute to this. The rest of panels show three main findings. First, on average individuals display poor performance (both in terms of raw and risk-adjusted returns) when compared against the pension funds. Second, there is considerable heterogeneity in performance across individuals. Third, as we move from Group 1 (panel b) to the Group 4 (panel d), we can see that average performance worsens and dispersion in performance increases.

TABLE (3) AROUND HERE

[11] We discarded the use of Sharpe's ratio because in our sample excess returns tend to be negative. This makes the interpretation of the ratio less clear. Indeed, an individual with negative excess return and a low risk strategy would appear with a lower ratio than an individual with a more negative excess return and with a riskier strategy.

[12] MSCI Chilean stock index.

There are some factors behind this lacklustre performance. First, at the beginning of our sample, most members who made voluntary changes were in funds A, B and C. Moreover, they made very few changes. Indeed, the majority (26.6%) only made one change, 72% made less than 5 changes, and only 15% made more than ten changes. Therefore, their performance was somewhat similar to the one obtained by these three funds. Second, between 2007 and 2016 Fund A had the worst performance (lowest average return and highest volatility) whereas funds B and C also performed poorly. As a result, the majority of members with fund changes obtained poor performance in this period. Considering risk-adjusted returns does not alter this result.

A relevant question regarding the good performance obtained by some individuals in our sample is whether this is due to the existence of skill or the product of luck. We shed light on this matter by examining the relation between the number of fund changes made by members and the performance they obtained. If there was true market-timing ability for a group of individuals, we should observe a relatively high number of fund changes coupled with good performance. Moreover, if individuals are particularly skilled at market timing, this group should exhibit a better performance versus the rest of members. Table (4) shows the mean and median number of voluntary fund changes according to the performance (quartiles) group and the type of member. Panel (a) shows the results by average raw return performance, while Panel (b) does so for abnormal returns performance groups. Two main results emerge. First, the presence of individuals with high number of fund changes (Group 4) is more (less) prevalent in the worst (best) performance groups, while the opposite pattern holds for those with few changes (Group 2). For Group 3 the distribution of individuals across performance groups is fairly constant. Second, overall, there is a statistically-significant negative relation between the number of fund changes and performance. This is, the groups with the worst (best) performance, measured as raw or as excess returns, present a higher (lower) number of fund changes. Nevertheless, this relationship is non-monotonic, as the number of changes slightly increases when moving to from the second-to-best performing group to the best-performance group, although this increase is non-significant for the market-timers.

TABLE (4) AROUND HERE

We interpret these results as suggesting that good performance is caused by luck rather than by ability. Unreported pooled OLS regressions show that there is a negative relationship between raw return and number of changes up to around 35 changes (only 0.2% of individuals made that many changes in our sample). From then on, the relationship becomes positive. However, an individual would have to make at least 66 changes in order to have the same expected return of making no fund changes. We will return to the issue of luck versus skill in our robustness analysis.

3.3 Evidence of Learning

We now focus on what leads individuals' to make fund changes. Since members of the pension plan cannot use their mandatory savings until retirement, trading for liquidity needs or tax considerations should not play a major role. However, two additional candidates could be playing a role. First, life-cycle considerations could be present. Second, market timing motives could also lead to make fund changes. If the first type of consideration is prevalent, it could be expected that, on average, fund changes would go in one direction, namely reducing equity exposure as individuals age. In the case of the second explanation, we would expect equity exposure to increase and decrease over time. This type of motivation seems particularly valid for the group of members with extreme increases and reductions in equity exposure and which we have labelled as "market timers".

We also hypothesize that individuals may be learning from past investment decisions. In order to test this, we build proxies for individuals' perceived ability. In order to to this, we considered two factors. First, when does a fund change qualify as a "successful" change? And second, how often should this evaluation take place?

Regarding the first issue, we explore three different definitions of success. Under definition 1, we classify a change as successful if the return is higher than the one that would have been obtained without the change and unsuccessful otherwise. This is a counter-factual exercise. Under definition 2, a change is successful if a positive return is obtained when the change is made and unsuccessful otherwise. We argue that this is a naive evaluation rule as a positive (negative) return obtained by picking one particular fund among five alternatives does not necessarily imply that a good (bad) decision was taken.[13] This rule is motivated by evidence on the literature suggesting that individuals tend to use heuristics or simplified rules when making financial decisions.[14] Our third definition declares a change as successful if the highest-return fund is selected and unsuccessful otherwise. We view this definition as following the spirit of what market timing practitioners aim to achieve. We leave out alternative definitions, such as risk-adjusted returns or abnormal returns, since it seems unlikely that the average member of the pension system is capable of estimating this performance measures.

As for the evaluation horizon, this could be at the least: daily, monthly, quarterly or yearly. From these possibilities, we use monthly evaluations. The reason for this is motivated by our institutional setup. The Pension Supervisor collects daily data on the NAV of pension funds. This data is available, with some lag, in the Supervisors' website. However, since only the daily NAVs are reported, if an individual who has made a fund change wishes to know, for instance, if he selected the best fund for a particular day, he would have to build daily returns series for each fund. Additionally, the first days of each month, the Supervisor publishes information on the returns earned by pension funds during the previous month (e.g. in the first days of December, the Supervisor announces the returns earned by pension funds during November). This information is available on the Supervisors' website, along with time series of monthly returns. Moreover, all major newspapers give wide dissemination to these results, with special emphasis on whether the returns obtained were positive or negative, rather than on the specific return figures.[15] Members of the pension system have an additional source of information, which is a balance sent to them by their PFM every

[13]Imagine, for instance, qualifying a decision to obtain a -1% return in an equity fund during 2008 as bad, when market returns were well below this figure.

[14]Barber and Odean (2013) label this simple learning rules as "reinforcement learning" and argue that, under this logic, individuals tend to repeat (avoid) behaviours that have coincided with pleasure (pain) in the past. Such form of learning has been documented in buy and sell decisions of individual stocks (Strahilevitz et al. 2011).

[15]Barber and Odean (2007) show that factors such as a stock receiving news coverage affect individuals' portfolio decisions.

4 months. This balance also has information on the returns earned during the January to April, May to August and September to December periods. However, data from the 2009 EPS shows that 37% of workers claims not having received such a statement from their PFM during the last 12 months. Moreover, from those who received their statement, only about one third claims that they read information about funds' returns. In the case of yearly or lower frequency evaluations, we argue that it seems unlikely that individuals are able to keep track of the fund change decisions they have made during such long periods of time. Based on these considerations, we choose to work with a monthly evaluation frequency.[16]

The final step in order to build our ability measures is to keep track of the total number of changes made and whether these changes were successful. Since there are three definitions for success, three measures of ability are built. Ability is defined each month as the proportion of successful over total accumulated changes.[17] Therefore, this is a variable that takes values between 0 (no successful changes) and 1 (all changes are successful). Since we do not have information on changes before February 2007, we assign all individuals in our sample initial values of 0.5 for their ability.[18] If no changes are made, the 0.5 value is kept. Also, the values are updated every month in which a fund change takes place.[19] Figure (2) shows the densities for our three ability measures at the end of our sample, along with the mean for each measure. Turning to our first definition of ability (Panel a) we have that, on average, Group 2 has the lowest ability (0.45), followed by the Group 3 (0.48) and 4 (0.59). Therefore, only for the last group average ex-post ability is higher than our assumed initial values of 0.5. The

[16]Nevertheless, all our qualitative results continue to hold if a daily evaluation frequency is used.

[17]This approach is consistent with rational individuals using a Bayesian updating process to estimate their ability. A previous version of this paper (available at `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3178948`) features a theoretical model where individuals update their ability in the same way in which we have built the empirical proxies. This model also features closed-formed results that allow it to make testable predictions regarding the incentives to engage make investment decisions. These results were used to guide our empirical strategy.

[18]In the case of Linnainmaa (2011) this issue is tackled by fitting a structural model to the data and deducing the individuals' prior of their ability. Given our approach, we lose precision in our estimates, since we are artificially reducing the range of variation in the initial values of ability to a single value of 0.5. This should bias the significance tests for the ability proxies towards accepting the null hypothesis of no effect of ability. Nevertheless, these effects turn out to be significant and sizeable.

[19]We explored an alternative way to construct ability as the number of successful changes minus total changes. Under this definition ability can take negative and positive values. All our conclusions continue to hold under this case. Even more, since in this case the proxy of ability has a wider range of variation, our regression results achieved better fits to the data.

density of ability measured using a naive evaluation is showed in Panel (b). In this case, the average ex-post estimated ability is very similar for Groups 2 and 3, reaching 0.58 and 0.6, respectively. In the case of Group 4, their average ability is considerably higher, reaching a value of 0.68. It is interesting to note that, under the naive evaluation rule, the density of the Group 4 is by far the most favourable. This is, if individuals do evaluate their changes using such a rule, members of this group would have a high assessment of their ability. Finally, we move to the market timing definition of ability in panel (c). Average ability for Group 4 is once again the highest, but it reaches a value of only 0.36. The average for Groups 2 and 3 are 0.35 and 0.3, respectively.[20]

FIGURE (2) AROUND HERE

Before using regression analysis, it is interesting to take a look at the correlations between ability and the total number of fund changes. These correlations are 0.17, 0.45 and -0.38 for our counter-factual, naive and market-timing ability measures, respectively. All these values are statistically significant and, as we will show, the signs of these correlations will continue to hold in our regressions.

We give preference to simple, panel linear models, in order to have a readier interpretation of the coefficients obtained in the regressions.[21] After performing standard specification tests, we estimated fixed-effects panels.[22] This has the advantage of allowing us to control for individual-level characteristics that are time-invariant and may be relevant to determine the propensity to make fund changes, but for which we do not have a proxy, such as intelligence (see, e.g. Grinblatt et al. 2012).

[20]The finding that ex-post estimated ability is the lowest under the market timing style evaluation is consistent with financial markets being efficient. Indeed, having the ability of foreseeing which of the five pension funds will have the highest return in any given month would be highly profitable.

[21]We also undertook our analysis using panel probit models. The specification tests indicated that random effects models would yield inconsistent estimates. Therefore, we ran fixed-effects panel probits. These models have the difficulty of pinpointing marginal impacts, as these depend on the fixed-effects values, which cannot be obtained from the estimations. We chose fixed effects values such that the predicted change values evaluated at the means of the dependent variables yielded estimations that were similar to the proportion of fund changes observed in our sample. Following this procedure, our qualitative results continue to hold.

[22]As a robustness check, we also performed random-effects estimations. While the tests carried out cast doubt on the consistency of these estimators, our main results continue to hold.

We study a total of three dependent variables: Change (equal to 1 if there is a fund change and 0 otherwise); More Risk (equal to 1 if there is an increase in equity exposure and 0 otherwise); and Less Risk (equal to 1 if there is a drop in equity exposure and 0 otherwise). The regression model and dependent variables are given by:

$$Y_{i,t} = \Gamma X_{i,t} + \gamma_i + \epsilon_{i,t} \tag{2}$$

where $X_{i,t}$ is a set of control variables, including ability; γ_i is an (unobserved) individual effect; and $\epsilon_{i,t}$ is a potentially correlated random term. The independent variables used are: the proxy for ability, both alone and interacted with the male variable, Age, natural logarithm of pension savings balance, natural logarithm of income, a dummy indicating if and individual made voluntary savings the previous month, another dummy indicating the existence of periods of unemployment, the lagged return of the fund in which the individual invests his savings, the lagged value of the difference in returns between funds A and E, an interaction between this lagged difference in returns and a dummy that takes the value of 1 for males and 0 otherwise, the lagged value of the standard deviation of fund A's returns, an interaction between this volatility and the male dummy, a dummy indication if the individual changed from manager, and a dummy indicating if the individual has an active web password to facilitate making a fund change. In order to control for the increasing frequency of fund changes over time, we include a quadratic trend. Moreover, to control for the investment recommendations given by financial advisor firms (see Da et al. 2018) we also include dummy and trend variables. This allows us to effectively isolate the effect of investors' individual learning experience through our ability proxies. We now discuss the expected effects of our control variables on the incentives to make fund changes.[23] We expect our ability proxies to have a positive effect on the incentives to make fund changes. Since learning about market timing ability is an investment, we expect its attractiveness to decline if there is less time to benefit from gaining this knowledge. Therefore, we expect age to have a negative effect on the

[23] All the expected effects can be theoretically motivated using a simple learning model similar to the one developed by Linnainmaa (2011). These results are available upon request.

incentives to make changes. It can be showed that higher wealth should lead to individuals making more (less) changes if they have low (high) risk aversion. Therefore, the signs of the savings balance and income can be both positive or negative. The inclusion of the voluntary savings dummy proxies for financial sophistication and is thus expected to have a positive sign. The gap in returns between funds A and E and the volatility in returns of fund A are proxies for the potential gains of market timing. Therefore, we expect them to have positive signs. The presence of the lagged return of the fund in which individuals invest their fund is included in order to control for the tendency of investors to chase past returns.[24] The introduction of the male dummy interaction seeks to capture differences in response to market variables and perceived ability across genders (Barber and Odean 2001 and Hibbert et al. 2016). The PFM dummy controls for the possibility that fund changes are made as the result of advice from a new PFM. Finally, the web-password dummy is also expected to have a positive sign since it indicates that individuals have a lower cost of requesting a fund change.

Table (5) shows the regression results for the Change variable. Given that fund changes are, on average, scarce events, our models have limited predictive power. Nevertheless, practically all variables are highly significant, both in individual terms and as a group. Interestingly, the best fit to the data, measured by the pseudo R^2 is achieved with the naive ability specification. Age has a significant and negative effect on the propensity of making fund changes, which is consistent with models in which trading is an investment that allows individuals to learn about their ability. Having a shorter period in which potential gains can be exploited makes learning less attractive. Under specification 2, each additional year translates into a drop of 0.034 percentage points (or 3.4 basis points) in the probability of making a fund change. We have a negative and significant effect of income across all specifications. However, this effect is small and translates in drop of up to 0.255 basis points in the probability of making a fund change in the presence of a 1% increase in income. Making voluntary pension savings increases the likelihood of changing funds by up to 1.21 percentage points (121

[24] Benartzi (2001) shows evidence that individuals tend to extrapolate good past performance far into the future for individual stocks. This could be an explanation for this type of investment style.

basis points) which is a large effect. One potential concern with this variable is that making voluntary savings should be the result of a decision-making process and therefore, it may be endogenous. We mitigate potential endogeneity issues by using the lagged value of this dummy.[25] Turning to r_{t-1}, our proxy for rear-view investing, we find a positive and significant effect, which we interpret as being consistent with the notion of individuals chasing past returns. A 1 percent increase in the return of the fund to which an individual later changes to, increases the likelihood of making such a change by about 2 basis points. The return gap between funds A and E, one of our proxies for the potential gains of market timing, has a negative and significant coefficient. In the case of females (males), a 1 percent increase in this gap reduces the likelihood of making a fund change by around 1.6 (2.1) basis points. Volatility, the second proxy for the attractiveness of market timing, does have the predicted positive sign across all specifications. We do not find large or robust evidence of statistically differences in response across genders for this variable. The economic importance of this proxy is similar to the returns gap. The Change PFM and Web Password dummies both have positive, statistically significant and economically relevant impacts on the likelihood of making fund changes: about 3.6 percentage points (360 basis points) and 2 percentage points (200 basis points), respectively. Turning to the ability variable, the first two empirical specifications show a positive impact of ability on the frequency of fund changes, while the third specification has a negative coefficient. In the case of the naive evaluation ability proxy (column 2) a one standard deviation increase in ability raises the probability of making a further change by 156 (177) basis points for females (males). The effects of perceived ability are thus economically relevant.

TABLE (5) AROUND HERE

We now proceed to analyse the results of the regressions that study the decision of increasing, as well as reducing equity exposure. All results are showed in Table (6). Since the signs of the coefficients in these regressions are the same for both decisions, we will make a

[25] Even so, the coefficients of the rest of variables are robust to using the current or lagged value of VPS or even to the exclusion of this variable from the regression.

joint analysis of the results, with an emphasis in comparing whether the response to changes in our dependent variable are more biased towards increasing or reducing exposure to equity. Regarding age, savings account balance and income, the results are very similar to those observed in our previous model. The voluntary savings dummy has a positive and significant signs across both tables and for all specifications. One interesting difference emerges for the r_{t-1} variable. While the coefficient is positive and significant for the reduced equity exposure case, it losses practically all its effect for the increase equity exposure case. Therefore, the evidence suggests that the past-return chasing motive is relevant when evaluating the decision of reducing equity exposure.[26] For females, the Delta_r variable lacks significance in terms of higher odds of increasing equity exposure. For males, it has a negative, but weakly-significant effect. This same variable has a negative effect on the likelihood of reducing equity exposure of about 1.7 (1.9) basis points for females (males). Regarding volatility, the coefficients have the same sign for the increase and reduce equity variables. However, once again we find differences in magnitudes. For females, a 1 percent increase in volatility leads to an increase of 0.397 basis points in the probability of increasing equity exposure. For males the point estimates are negative, suggesting less response, but these coefficients are not significant for all specifications. The same change in this variable has an impact of 0.866 basis points in the probability of reducing equity exposure for both females and males, suggesting a "shelter-seeking" behaviour among members of the system, who increase the odds of lowering equity exposure in the month following high volatility of fund A's returns.[27] Our findings regarding the negative effect of volatility on equity exposure are similar to those of Tang et al. (2012). An interesting finding emerges with the change PFM dummy. While changing manager has an associated increase of about 140 basis points in the odds of reducing equity exposure, this figure doubles to almost 220 basis points for the probability of increasing equity exposure, suggesting that, if some advice regarding equity exposure is given during this change, it is

[26] As we mentioned before, this type of conduct is consistent with the behaviour observed at the end of 2008 for some members of the pension system who, having suffered losses in funds with high equity exposure, decided to change to fund E, with the lowest equity exposure, which was the best-performing fund during that year.

[27] Recall that fund A has the highest equity exposure, reaching almost 80% of the total funds' portfolio.

biased towards encouraging members to increase their equity exposure. This pattern reverses for the web password dummy, which raises the probability of increasing (reducing) equity exposure by 67 (100) basis points. When ability is measured using a counter-factual evaluation, a one standard deviation increase would lead to an increase of 46.5 (58.2) basis points in the probability of increasing equity exposure for females (males). This same change translates in an increase of 22 basis points in the probability on reducing equity exposure for both genders. Moreover, when ability is measured using the naive evaluation, the same change raises the probability of increasing equity exposure by 70.5 (83.5) basis points for females (males), while also increasing in 85.5 basis points the probability of reducing exposure for both genders. Once again, the coefficient of our ability variable built using market-timing criteria has a negative effect.

TABLE (6) AROUND HERE

To sum up, our regression results are largely consistent with our prior for the case of the age and web password variables, our proxies for investment horizon and the cost of making fund changes, respectively. For the case of our measures of wealth and income, the results are less consistent. We find some evidence consistent with past-return chasing being an additional reason to change type of fund when it accompanies a reduction in equity exposure. We also find that the volatility of returns, which proxies for the potential gains of engaging in market timing has a positive effect on fund changes. Our key variable, ability, has the expected sign for two of our three proxies. We view this finding as robust evidence of the existence of a feedback effect between perceived skill and subsequent fund changes. The proxy that seems to provide a better fit to actual data is the naive evaluation rule, which is consistent with previous literature showing the relevance of simplified rules to assess performance and make financial decisions. When a market timing evaluation rule is used, ability has the wrong sign. Rather than this proxy having a negative causality on fund changes, our interpretation of this finding is that individuals use a naive investment rule to evaluate their performance and this rule happens to be negatively correlated with the market timing rule in our sample.[28]

[28] The correlation between the final values of ability using these two evaluation rules is -0.15. This correlation

Finally, in terms of differences across genders, we find that males are more influenced by their perceived ability.

3.4 Robustness and Additional Analysis

Results for different cohort of members

One potential limitation in our analysis is due to our inability to observe fund changes prior to 2007. Since the individuals in our sample were already members of the Pension System by 2007 it is possible that they had previous learning experience. Therefore, by setting initial ability at the same level, we would be biasing this variable, artificially reducing its variance in the starting point in our sample. While we argue that this should bias our estimated coefficient towards zero, we also performed our analysis for a sample of members who joined the system during the second half of 2007.

This new sample is formed by 13,986 individuals. Compared to the characteristics of our original sample reported in Table (1), this cohort is much younger (average age is 26 versus 40 for original sample); they have lower accumulated avarage balance (about 90% lower versus original sample); and they have smaller wages (about 25% lower versus original sample). All these differences are consistent with these individuals having just joined the system.

Tables (7) and (8) reproduce the results of Tables (5) and (6) for the 2007 cohort, respectively. The main difference in terms of our ability measures is that the counter-factual variable now displays a negative effect on the probability of making fund changes. Nevertheless, the naive ability measure continues to display a positive sign. Regarding the effects of ability on the propensity to take on more or less risk, once again the counter-factual variable now has a negative sign. In the case of our naive variable, we find and assymetric effect. Indeed, increases in perceived ability predict higher chances of increasing risk (i.e. increasing equity exposure). However, the effect is weaker in terms of lowering equity exposure. In fact, the impact is only significant (at the 10% level) for males.

Overall, applying our analysis to a group of individuals for whom we have a complete

is statistically different from zero at the 1% level.

history produces some minor effects. Once we are able to take into account all the fund changes made by this group, we find that our results for two out of three ability measures continue to hold. Namely, the naive and market-timing measures display the same signs and similar significance levels from our original sample. Only for the counter-factual ability measure we find a change in the predicted effect. Taking this evidence into account, we argue that our conclusions about the presence of feedback effects for members of the system is fairly robust.

Alternative definitions of learning

In order to further shed light on the robustness of the learning effects in our study, we modified our ability variable. Instead of building this variable as the percentage of previous successful changes over total changes, we use a dummy variable taking the value of 1 if a fund change has been "successful" and 0 otherwise. As in our previous analysis, we employ three different definitions of success (counter-factual, naive and market-timing). By doing this, we avoid using a potentially biased variable. Our results (available upon request) are not qualitatively affected. Moreover, the naive definition continues to have the highest predictive power in terms of explaining fund changes.

Performance and learning in a different time period

Since our sample period contains the negative effects of the Sub-prime Crisis, we explore the robustness of our findings using different samples. If we focus on the 2009-2016 period, Fund A is the most volatile but also has the best performance, with a 8.1% annualized average return and 9.1% standard deviation. Funds B, C, D and E follow, with average returns of 7.2%, 6.5%, 5.9% and 5.4%, respectively; and standard deviations of 6.6%, 4.3%, 2.5% and 1.8%, respectively.[29] Moreover, once again there are large groups of members around funds A, B and C. Given the good performance achieved by these funds, all our groups of individuals with fund changes achieve average returns (both raw and abnormal) that are usually at least

[29]When abnormal returns are estimated we obtain a similar risk-return trade-off.

as good as those of fund B, suggesting that the performance obtained is sample-dependent.

Nevertheless, several of our key findings continue to hold in this case. First, the negative relation between number of fund changes and performance is still present. Second, the qualitative findings of our regression analysis continue to hold. Examining different sub-samples yields similar qualitative results. The details of these results are available upon request.

Simulating Performance

In order to shed further light on the issue of whether skill or luck are the main drivers of the results achieved by the best-performance group, we follow a procedure along the lines of Bajgrowicz and Scaillet (2012). Specifically, we estimate the investment rules followed by the best and worst performers in our data. We then simulate the investment decisions that would result for each rule and compare the distributions of returns obtained in order to assess differences in performance.

In order to estimate the investment rules, we discretize the dependent variable in a total of eight categories: from -4 to 4. An individual that moves to a fund with less equity is assigned a negative number. In particular, -4 is the lowest number possible, and it corresponds to moving from fund A to fund E. On the other hand, 4 is the highest number possible, representing an investor that changes from fund E to fund A. The baseline case is 0, i.e. no fund change. This variable is modelled using a multinomial logit model. We maintain the same set of controls.[30]

After estimating the investment rules we generate 1,000 different return histories for funds A to E, as well as the GARCH standard deviation of these returns. We also simulate R_m and R_f. The returns are generated through a bootstrapping procedure, avoiding the need to make ex ante assumptions about the distributions for the returns. We apply the estimated decision

[30]An alternative methodological choice would have been to model the type of fund chosen. We discard this type of specification because we are interested in modelling the actual fund change choices, rather than deriving the changes implicit in the choice of pension fund. Also, when modelling fund changes, we ruled out the possibility of using an ordered probit model, which seems intuitive given the ordering of our dependent variable in terms of equity exposure. However, the specification tests performed showed that these models violated key assumptions, such as the proportional odds assumption, casting doubt on the consistency of the results. This is related to our dependent variable being heavily biased towards taking only one of the nine possible values, which is no fund change. Given this, we opted for the multinomial specification, which provides consistent albeit inefficient estimates. All these results are available upon request.

models to each of the returns paths. This allows us to calculate the average return and alpha obtained, as well as the empirical distribution for these variables. We omit the corresponding output and merely note that the distributions obtained are quite similar for both rules. Indeed, in our sample the average alpha for the best performing group was 3.56% and it only reached 1.63% for the worst performance group. However, the simulated average annualized alpha for the best and worst performance groups are 0.6511% and 0.6443%, respectively.

Market Timing Firms and Fund Changes

Recently, some firms that sell advice regarding the best moment to change between pension funds have gained notoriety. In exchange for a monthly fee, these firms send announcements to subscribers, recommending fund changes, which typically involve a considerable adjustment in equity exposure (e.g. changes from Fund A to Fund E or vice versa) and are aimed at achieving market timing.[31]

We have already controlled for the presence of this advice in all our regressions. However, as a robustness analysis, we check if our conclusions are sensitive to the presence of members that follow these announcements. We have information on the date and advised equity adjustments for thirty-two announcements that took place between 2011 and 2016. Using this information we find that for 255 individuals (6.2% of those with one or more fund change) there is at least one match in dates. Excluding this group does not affect our results. This lack of relevance seems to contrast with the evidence of Da et al. (2018), who report a significant impact on the price of some domestic financial instruments following these announcements. Our data provides a possible explanation, since among the 255 individuals who have followed the firms' advice, only 14 of them (0.4% of individuals with at least one fund change in our sample) have done so for more than half of their changes. This suggests that the price effects are not driven by a large group composed by the same individuals, who consistently follow market timing recommendations. Rather, it seems that the increasing number of fund changes is fuelled by "newcomers".

[31]Da et al. (2018) provide details on the way in which these firms operate.

4 Conclusions

In this paper we characterize those members of the Chilean DC pension system that make fund changes, assess the performance of their decisions and identify if they learn from their past investment decisions.

Our evidence shows that the average performance obtained by individuals who make fund changes is poor, although this finding is influenced by the low returns experienced during the Sub-prime Crisis. Nevertheless, there is robust evidence that performance is decreasing in the number of fund changes made, regardless of the sample period. This supports the view that skill is not the main driver behind good performance. Additionally, our analysis involving simulated returns casts further doubt on the existence of true investment skills in our sample.

We have documented the presence of a sizeable feedback effect between perceived ability and the subsequent likelihood to make more fund changes. However, the direction of this relation is positive when past changes are evaluated according to naive and counter factual rules.

Taken together, our findings suggest that part of fund changing activity observed in our data may be explained by individuals chasing market-timing strategies. Moreover, these individuals appear to use simplified and inadequate rules in order to evaluate the success of past decisions. From a policy stand, our results suggest that the advantages of having flexibility in the way in which funds can be invested should be weighed against the actual outcomes obtained by members who are making frequent use of these possibilities. Moreover, improving our understanding of the way in which individuals learn about the consequences of their investment decisions seems like an interesting and relevant research avenue, with potential implications beyond the scope of pension systems.

A Figures and Tables

Figure 1: Monthly Fund Changes

Source: Authors' calculations based on Supervisor's data. The left axis shows the monthly number of voluntary fund changes made by individuals in our sample. The right axis shows the percentage of voluntary fund changes that correspond to extreme reductions (changes from Fund A to Fund E) and increases (changes from Fund E to Fund A) in equity exposure.

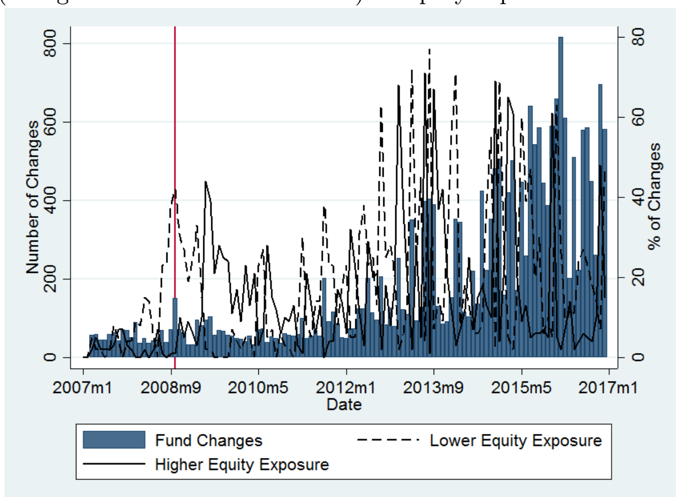
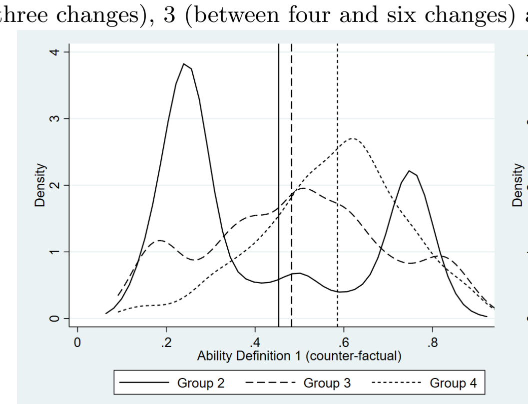
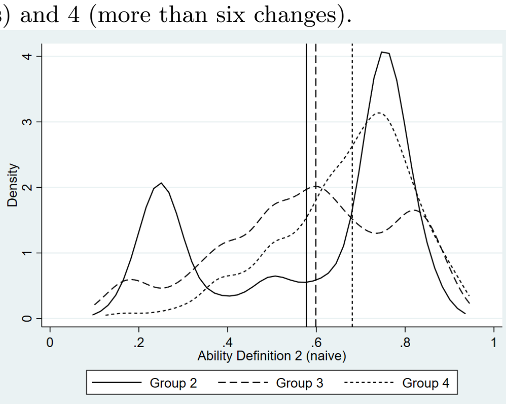


Figure 2: Density of Ability Measures

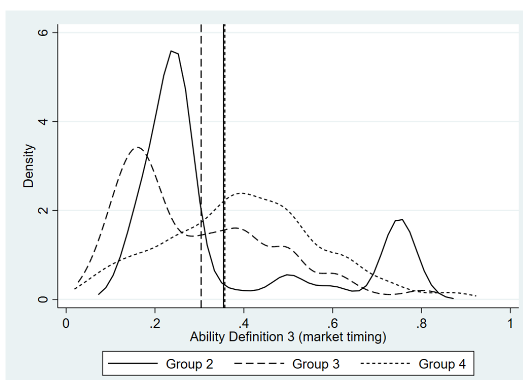
Source: Authors' estimations. These panels show the density at the end of our sample for three different measures of ability. Each density is accompanied by a vertical line showing the mean of the distribution. Panels (a), (b) and (c) plot this relation for ability assessed according to definitions 1, 2 and 3, respectively. Definition 1, labelled "counter-factual" qualifies a fund change as successful if the return is higher than the one that would have been obtained without making the change and unsuccessful otherwise. Definition 2, called "naive" qualifies a fund change as successful if a positive return is earned during the month in which the change was made and unsuccessful otherwise. The 3rd definition, labelled "market timing" states that a change is successful if the highest-return fund for that month is selected and unsuccessful otherwise. The densities are showed for groups 2 (up to three changes), 3 (between four and six changes) and 4 (more than six changes).



(a) Definition 1 (counter-factual)



(b) Definition 2 (naive)



(c) Definition 3 (market timing)

Table 1: Descriptive Statistics

Source: Authors' estimations. This table shows the means values for our sample, which is composed of 62,760 individuals. The sample is divided in four groups: Group 1 (individuals with no voluntary fund changes); Group 2 (individuals with one to three fund changes); Group 3 (individuals with four two six fund changes); and Group 4 (individuals with more than six fund changes). ***, ** and * denote that the mean of groups 2, 3 or 4 are different, at the 1%, 5% or 10% significance level, versus the mean of group 1. The data covers from February 2007 to December 2016. Age is measured in years. log(Balance) is the natural logarithm of total savings, including both mandatory and voluntary account balances, measure in Chilean pesos (1 USD equals 660 CLP). log(Income) is the natural logarithm of monthly income, measured in Chilean pesos. VPS takes the value of 1 (0) for periods in which individuals made (did not make) voluntary pension savings. Unemployment takes the value of 1 (0) for periods without (with) mandatory contributions. Male takes the value of 1 (0) for males (females). Change takes the value of 1 for periods in which the individual made a voluntary fund change and 0 otherwise. More Risk (Less Risk) takes the value of 1 if the individual made a voluntary fund change that increased (lowered) his equity exposure and 0 otherwise. Equity is the weighted mean equity exposure in both mandatory and voluntary accounts, expressed in percentage of total savings. Change PFM takes the value of 1 if the individual changed from pension fund manager during that month and 0 otherwise. Web Password takes the value of 1 if an individual had obtained the password that is required in order to make fund changes through a PFM's website and 0 otherwise. N represents the number of individuals in each group.

Variable	Group 1	Group 2	Group 3	Group 4
Age	41.212	39.392***	42.108***	40.688***
log(Balance)	14.675	15.729***	16.164***	16.369***
log(Income)	12.174	13.069***	13.289***	13.604***
VPS	0.034	0.106***	0.173***	0.283***
Unemployment	0.197	0.129***	0.114***	0.089***
Male	0.55	0.592***	0.597***	0.671***
Change	0	0.015***	0.039***	0.121***
Cumm Changes	0	0.415***	1.586***	3.986***
More Risk	0	0.003***	0.013***	0.058***
Less Risk	0	0.012***	0.026***	0.063***
Equity	49.365	58.56***	53.124***	52.371***
Change PFM	0.004	0.008***	0.012***	0.013***
Web Password	0.066	0.216***	0.347***	0.535***
N	58,602	2,353	797	1,008

Table 2: Type of Fund Changes

Source: Authors' estimations. This table shows the frequency and percentage of fund changes by group of individuals. For instance, Group 4 (formed by individuals with more than six changes) did not make a fund change almost 88% of the time. This group made a total of 22,403 changes. A total of 28.54% of these changes were strong reductions in equity exposure. Also, 23.86%

Type of Change	Group 1	Group 2	Group 3	Group 4	Total
-4	0%	18.75%	15.03%	28.54%	5,485
-3	0%	16.29%	7.64%	5.41%	1,747
-2	0%	21.66%	16.56%	13.05%	3,412
-1	0%	21.83%	27.27%	5.07%	2,657
0	100%	98.52%	96.08%	87.88%	7,444,515
1	0%	10.25%	8.23%	4.74%	1,420
2	0%	5.61%	11.43%	15.14%	2,858
3	0%	1.81%	3.20%	4.20%	804
4	0%	3.80%	10.65%	23.86%	4,020
Total changes	0	4,155	3,719	14,529	22,403

Table 3: Active Investors and Pension Fund Performance (%)

Source: Authors' estimations. This table summarizes the performance obtained by members with at least one fund change and that of pension funds. The second column shows the annualized average return, the third column shows annualized standard deviation and the last column contains the annualized abnormal return (alpha). Panel (a) shows the results for the five pension funds. Panel (b) contains the results for the individuals in Group 2, showing 5th and 25th percentiles, followed by the mean and the 75th and 95th percentiles for each performance measure. Panels (c) and (d) show similar information for individuals in Groups 3 and 4, respectively.

	(a) Pension Funds				(b) Group 2		
Fund	Return	SD	Alpha		Return	SD	Alpha
A	2.678	10.923	2.791	P5	2.018	5.007	2.077
B	3.314	7.904	3.083	P25	2.536	7.533	2.603
C	4.013	5.136	3.575	Mean	3.012	8.356	2.874
D	4.433	2.893	3.961	P75	3.399	10.62	3.184
E	4.817	1.723	4.39	P95	4.019	10.9	3.635
	(d) Group 3				(c) Group 4		
	Return	SD	Alpha		Return	SD	Alpha
P5	0.833	4.701	0.749	P5	0.506	5.141	0.392
P25	2.318	6.85	2.318	P25	1.794	7.337	1.78
Mean	2.848	8.016	2.683	Mean	2.429	8.35	2.301
P75	3.471	9.913	3.207	P75	3.132	10.09	2.934
P95	4.045	10.676	3.71	P95	4.086	10.502	3.818

Table 4: Relation between number of fund changes and performance

Source: Authors' estimations. The upper part of this table shows the number of individuals from Group 1, 3 and 4 that are present in each performance category, defined according to the quartiles of the raw average returns distribution for individuals with at least one fund change. The table also shows the average number of fund changes for each group. ***, ** and * denote that the mean number of changes between adjacent performance groups are different, at the 1%, 5% or 10% significance level. The lower part of the table displays the same information, but performance groups are formed according to the abnormal return (alpha) obtained by individuals.

	Group 2		Group 3		Group 4	
Return Group	N	No. of Changes	N	No. of Changes	N	No. of Changes
Cat. 1 ($r < 2.37\%$)	608	1.86	253	4.55	177	13.6
Cat. 2 ($2.37\% < r < 2.95\%$)	734	1.63***	164	4.56	141	12.46**
Cat. 3 ($2.95\% < r < 3.37\%$)	658	1.64	157	4.70	225	13.90
Cat. 4 ($3.37\% > r$)	353	2.09	223	4.84	465	15.53
	Group 2		Group 3		Group 4	
Alpha Group	N	No. of Changes	N	No. of Changes	N	No. of Changes
Cat. 1 ($\alpha < 2.37\%$)	624	1.84	231	4.54	183	13.5
Cat. 2 ($2.37\% < \alpha < 2.82\%$)	736	1.61***	182	4.57	121	12.4*
Cat. 3 ($2.82\% < \alpha < 3.16\%$)	686	1.68	164	4.66	190	13.2
Cat. 4 ($3.16\% < \alpha$)	307	2.15	220	4.87	514	15.6

Table 5: Change Models

Source: Authors' estimations. This table shows the fixed-effects panel regression results for the binary Change/No Change dependent variable. ***, ** and * denote that coefficients are statistically different from zero at the 1%, 5% and 10% significance levels, respectively. The data covers from February 2007 to December 2016. Column (1) considers our counter-factual definition of ability whereas in columns (2) and (3) the naive and market-timing definitions or ability are used, respectively. Age is measured in years. log(Balance) is the natural logarithm of total savings, including both mandatory and voluntary account balances, measure in Chilean pesos. log(Income) is the natural logarithm of monthly income. VPS is the one-month lag of a dummy variable that takes the value of 1 (0) for periods in which individuals made (did not make) voluntary pension savings. Unemployment equals 1 for months without mandatory contributions and 0 otherwise. Delta_r represents the one-month and 36 months lagged differences in the monthly returns of funds A and E, expressed in percentage. Volatility is the one month-lagged GARCH standard deviation of fund A's monthly returns, expressed in percentage. Male takes the value of 1 (0) for males (females). Change PFM takes the value of 1 if the individual changed from pension fund manager during that month and 0 otherwise. Web Password takes the value of 1 if an individual had obtained the password that is required in order to make fund changes through a PFM's website and 0 otherwise. The regression includes dummies and trends to control for investment recommendations made by financial advisors.

	(1)	(2)	(3)
	Change	Change	Change
Ability	0.139***	0.312***	-0.222***
Male×Ability	0.0447**	0.0424**	0.00239
Age	-0.000637***	-0.000502***	-0.000570***
log(Balance)	0.000547***	0.000518***	0.000715***
log(Income)	0.000398***	0.000315***	0.000331***
VPS	0.0120***	0.00908***	0.00916***
Change PFM	0.0355***	0.0348***	0.0348***
Web Password	0.0227***	0.0178***	0.0209***
Unemployed	0.00546***	0.00436***	0.00473***
$\text{Unemployed}_{\text{start}}$	0.000912***	0.000838***	0.000808***
$\text{Unemployed}_{\text{end}}$	0.000307	0.000129	0.000178
$Delta_{r,t-1}$	-0.000231***	-0.000238***	-0.000251***
Male×$Delta_{r,t-1}$	-2.80e-05***	-3.41e-05***	-2.84e-05***
$Delta_{r,36}$	0.000272***	0.000282***	0.000311***
Male×$Delta_{r,36}$	4.33e-05	4.81e-05	-2.27e-06
Volatility	0.000102***	0.000109***	0.000117***
Male×Volatility	-5.03e-05***	-1.12e-05	-5.59e-05***
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Trend	Yes	Yes	Yes
$R^2(\%)$	1.9	4.1	2.4
N	7,403,126	7,403,126	7,403,126

Table 6: More Risk and Less Risk Models

Source: Authors' estimations. This table shows the fixed-effects panel regression results for the binary More Risk/No Change and Less Risk/No Change variables. ***, ** and * denote that coefficients are statistically different from zero at the 1%, 5% and 10% significance levels, respectively. The data covers from February 2007 to December 2016. Column (1) and (4) considers our counter-factual definition of ability whereas in columns (2) and (5); and (3) and (6) the naive and market-timing definitions or ability are used, respectively. Age is measured in years. log(Balance) is the natural logarithm of total savings, including both mandatory and voluntary account balances, measure in Chilean pesos. log(Income) is the natural logarithm of monthly income. VPS is the one-month lag of a dummy variable that takes the value of 1 (0) for periods in which individuals made (did not make) voluntary pension savings. Unemployment equals 1 for months without mandatory contributions and 0 otherwise. Delta$_r$ represents the one-month and 36 months lagged differences in the monthly returns of funds A and E, expressed in percentage. Volatility is the one month-lagged GARCH standard deviation of fund A's monthly returns, expressed in percentage. Male takes the value of 1 (0) for males (females). Change PFM takes the value of 1 if the individual changed from pension fund manager during that month and 0 otherwise. Web Password takes the value of 1 if an individual had obtained the password that is required in order to make fund changes through a PFM's website and 0 otherwise. The regression includes dummies and trends to control for investment recommendations made by financial advisors.

	(1)	(2)	(3)	(4)	(5)	(6)
	More Risk	More Risk	More Risk	Less Risk	Less Risk	Less Risk
Ability	0.0933***	0.141***	-0.0708***	0.0452***	0.170***	-0.151***
Male×Ability	0.0232**	0.0256**	-0.00277	0.0215*	0.0168	0.00516
Age	-0.000370***	-0.000302***	-0.000340***	-0.000268***	-0.000200***	-0.000230***
log(Balance)	0.000202***	0.000202***	0.000279***	0.000345***	0.000316***	0.000436***
log(Income)	0.000154***	0.000116***	0.000133***	0.000244***	0.000199***	0.000198***
VPS	0.00538***	0.00414***	0.00465***	0.00660***	0.00494***	0.00451***
Change PFM	0.0213***	0.0210***	0.0211***	0.0142***	0.0138***	0.0137***
Web Password	0.00882***	0.00669***	0.00850***	0.0139***	0.0111***	0.0124***
Unemployed	0.00219***	0.00169***	0.00198***	0.00327***	0.00267***	0.00275***
Unemployed$_{\text{start}}$	0.000250*	0.000214	0.000213	0.000661***	0.000624***	0.000595***
Unemployed$_{\text{end}}$	-0.000465***	-0.000550***	-0.000510***	0.000772***	0.000679***	0.000688***
$Delta_{r,t-1}$	2.94e-05***	2.42e-05***	1.93e-05***	-0.000260***	-0.000262***	-0.000270***
Male×$Delta_{r,t-1}$	-7.48e-06	-1.05e-05**	-7.67e-06	-2.05e-05***	-2.36e-05***	-2.07e-05***
$Delta_{r,36}$	-5.32e-05	-3.93e-05	-2.43e-05	0.000325***	0.000322***	0.000336***
Male×$Delta_{r,36}$	-0.000104***	-0.000107***	-0.000127***	0.000147***	0.000155***	0.000125***
Volatility	3.49e-05***	3.94e-05***	4.30e-05***	6.70e-05***	6.93e-05***	7.36e-05***
Male×Volatility	-2.98e-05***	-1.12e-05	-3.28e-05***	-2.05e-05	2.50e-08	-2.31e-05
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes	Yes	Yes
R^2	1.2	2.0	0.9	0.8	2.0	1.5
N	7,403,126	7,403,126	7,403,126	7,403,126	7,403,126	7,403,126

Table 7: Change Models - 2007 Cohort

Source: Authors' estimations. This table shows the fixed-effects panel regression results for the binary Change/No Change dependent variable. ***, ** and * denote that coefficients are statistically different from zero at the 1%, 5% and 10% significance levels, respectively. The data covers from February 2007 to December 2016. Column (1) considers our counter-factual definition of ability whereas in columns (2) and (3) the naive and market-timing definitions or ability are used, respectively. Age is measured in years. log(Balance) is the natural logarithm of total savings, including both mandatory and voluntary account balances, measure in Chilean pesos. log(Income) is the natural logarithm of monthly income. VPS is the one-month lag of a dummy variable that takes the value of 1 (0) for periods in which individuals made (did not make) voluntary pension savings. Unemployment equals 1 for months without mandatory contributions and 0 otherwise. Delta_r represents the one-month and 36 months lagged differences in the monthly returns of funds A and E, expressed in percentage. Volatility is the one month-lagged GARCH standard deviation of fund A's monthly returns, expressed in percentage. Male takes the value of 1 (0) for males (females). Change PFM takes the value of 1 if the individual changed from pension fund manager during that month and 0 otherwise. Web Password takes the value of 1 if an individual had obtained the password that is required in order to make fund changes through a PFM's website and 0 otherwise. The regression includes dummies and trends to control for investment recommendations made by financial advisors.

	(2)	(1)	(3)
	Change	Change	Change
Ability	-0.169***	0.0766***	-0.0693***
Male×Ability	-0.0569**	0.105***	-0.0878***
Age	0.000872***	0.000851***	0.000848***
log(Balance)	0.00245***	0.00268***	0.00258***
log(Income)	0.00315***	0.00353***	0.00338***
VPS	0.0397***	0.0394***	0.0372***
Change PFM	0.149***	0.152***	0.151***
Web Password	0.0409***	0.0442***	0.0427***
Unemployed	0.0357***	0.0402***	0.0384***
$\text{Unemployed}_{\text{start}}$	0.000438	0.000462	0.000445
$\text{Unemployed}_{\text{end}}$	0.00177***	0.00159***	0.00167***
$Delta_{r,t-1}$	-0.00423**	-0.00489**	-0.00387*
Male×$Delta_{r,t-1}$	-0.00157	-0.00250	-0.00230
$Delta_{r,36}$	-0.000499	-0.000556	-0.000511
Male×$Delta_{r,36}$	-3.23e-05	-0.000163	-4.24e-05
Volatility	0.213***	0.208***	0.201***
Male×Volatility	-0.0585	-0.0362	-0.0308
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Trend	Yes	Yes	Yes
R^2	5.4	5.1	5.1
N	1,538,723	1,538,723	1,538,723

Table 8: More Risk and Less Risk Models - 2007 Cohort

Source: Authors' estimations. This table shows the fixed-effects panel regression results for the binary More Risk/No Change and Less Risk/No Change variables. ***, ** and * denote that coefficients are statistically different from zero at the 1%, 5% and 10% significance levels, respectively. The data covers from February 2007 to December 2016. Column (1) and (4) considers our counter-factual definition of ability whereas in columns (2) and (5); and (3) and (6) the naive and market-timing definitions or ability are used, respectively. Age is measured in years. log(Balance) is the natural logarithm of total savings, including both mandatory and voluntary account balances, measure in Chilean pesos. log(Income) is the natural logarithm of monthly income. VPS is the one-month lag of a dummy variable that takes the value of 1 (0) for periods in which individuals made (did not make) voluntary pension savings. Unemployment equals 1 for months without mandatory contributions and 0 otherwise. Delta$_r$ represents the one-month and 36 months lagged differences in the monthly returns of funds A and E, expressed in percentage. Volatility is the one month-lagged GARCH standard deviation of fund A's monthly returns, expressed in percentage. Male takes the value of 1 (0) for males (females). Change PFM takes the value of 1 if the individual changed from pension fund manager during that month and 0 otherwise. Web Password takes the value of 1 if an individual had obtained the password that is required in order to make fund changes through a PFM's website and 0 otherwise. The regression includes dummies and trends to control for investment recommendations made by financial advisors.

	(1)	(2)	(3)	(4)	(5)	(6)
	More Risk	More Risk	More Risk	Less Risk	Less Risk	Less Risk
Ability	-0.0695***	0.0439***	-0.0487***	-0.177***	0.000176	-0.0594***
Male×Ability	-0.0343***	0.0465***	-0.0340***	-0.0180	0.0326**	-0.0377***
Age	-0.000256**	-0.000266**	-0.000269**	0.00171***	0.00170***	0.00170***
log(Balance)	0.000912***	0.00101***	0.000947***	0.00125***	0.00149***	0.00140***
log(Income)	0.000310***	0.000467***	0.000375***	0.000568***	0.00104***	0.000860***
VPS	0.0118***	0.0113***	0.00985***	0.0116***	0.0140***	0.0107***
Change PFM	0.0577***	0.0591***	0.0586***	0.0879***	0.0913***	0.0906***
Web Password	0.0105***	0.0117***	0.0108***	0.0157***	0.0205***	0.0183***
Unemployed	0.00348***	0.00531***	0.00422***	0.00630***	0.0119***	0.00972***
Unemployed$_{\text{start}}$	0.000106	0.000115	0.000103	0.000116	0.000147	0.000129
Unemployed$_{\text{end}}$	0.000966***	0.000890***	0.000933***	0.000634***	0.000472**	0.000523***
$Delta_{r,t-1}$	0.00253***	0.00210**	0.00257***	-0.000353	-0.000523	-0.000225
Male×$Delta_{r,t-1}$	0.000106	-0.000146	0.000151	-0.00444**	-0.00489***	-0.00484***
$Delta_{r,36}$	-0.000461***	-0.000487***	-0.000445***	-0.000658***	-0.000681***	-0.000662***
Male×$Delta_{r,36}$	-0.000109	-0.000179	-0.000153	0.000225	0.000168	0.000188
Volatility	0.0505***	0.0505***	0.0501***	0.138***	0.133***	0.131***
Male×Volatility	-0.0248*	-0.0193*	-0.0240*	-0.0131	0.00402	0.00502
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes	Yes	Yes
R^2	3.0	2.8	2.9	4.7	3.6	3.8
N	1,538,723	1,538,723	1,538,723	1,538,723	1,538,723	1,538,723

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