Coordinated Noise Trading: Evidence from Pension Fund Reallocations*

Zhi Da†
Mendoza College of Business
University of Notre Dame

Borja Larraín‡
Business School
Pontificia Universidad Católica de Chile

Clemens Sialm§
McCombs School of Business
University of Texas at Austin

Jose Tessada¶
Business School
Pontificia Universidad Católica de Chile

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Abstract

We document a novel channel through which coordinated noise trading exerts externalities on financial markets dominated by institutional investors. We exploit a unique set of events where Chilean pension fund investors followed an influential financial advisory firm that recommended frequent reallocations between equity and bond funds. The recommendations, which mostly followed short-term return trends, generated large and coordinated fund flows. Since the advisory firm gained popularity through social media, young investors were more likely to follow the recommendations and to reallocate their retirement savings. The fund flows resulted in substantial price pressure and increased volatility in both the equity and bond markets. Pension funds reduced their holdings of illiquid securities and increased cash holdings as a response to these flows. Our findings suggest that giving retirement savers unconstrained reallocation opportunities may destabilize financial markets and impose social costs on market participants.

Key Words: Coordinated Noise Trading, Pension Funds, Price Pressure, Financial Advisors, Social Media

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†239 Mendoza College of Business, University of Notre Dame, Notre Dame IN 46556. Tel: (574) 631-0354, and e-mail: zda@nd.edu.

‡Escuela de Administración and FinanceUC, Pontificia Universidad Católica de Chile, e-mail: borja.larrain@uc.cl

§McCombs School of Business and NBER, University of Texas at Austin, Austin, TX, 78712, e-mail: clemens.sialm@mccombs.utexas.edu

¶Escuela de Administración and FinanceUC, Pontificia Universidad Católica de Chile, e-mail: jtessada@uc.cl

1 Introduction

The impact of noise traders on asset prices is central to the debate over market efficiency. Black (1986) points out in his AFA presidential address that noise might cause market inefficiencies. DeLong, Shleifer, Summers, and Waldmann (1990a) formalize the role of noise traders in financial markets. They show that noise traders can create mispricing and excess volatility if the trading horizon of risk-averse arbitrageurs is short. On the other hand, there is an ongoing debate regarding whether noise traders can survive in the long-run and continue to affect asset prices (e.g., Kogan, Ross, Wang and Westerfield, 2006, 2009). Taking advantage of several unique features of the Chilean pension system, we document a novel channel where coordinated noise trading can exert large price pressure in both equity and bond markets, even when asset ownership is dominated by institutional investors.

The Chilean pension system is a fully funded defined contribution (DC) pension system with personal retirement accounts.[1] Currently, 70% of Chilean workers contribute 10% of their salary to the system. As a result, the pension assets are substantial, holding assets worth USD 150 billions, which correspond to around 60% of the GDP. Close to 30% of the Chilean stock market free float and 30% of the Chilean government bond market are held by the pension funds. Investors can freely choose how to allocate their balances across funds with different risk levels.

The volatile equity market in 2008 prompted many investors to attempt to "time" the market by switching their investments between funds primarily invested in equity and fixed income securities. An investment advisory firm called "Felices y Forrados" (FyF, translated as "Happy and Loaded") started in 2011 to cater to the popular demand for market timing. For a small fee of about six cents per day, FyF sends investors their switching recommendation by e-mail or private website login. Due to an aggressive marketing campaign on social media, FyF gained popularity among Chilean pension investors since 2012. As a result, recommendations from FyF have worked as a coordination device among noise traders. This is evident from Figure 1, which shows the number of voluntary daily fund switches since 2011. The spikes in the number of account switches closely coincide with the FyF recommendations. These account switches involve large fund flows, amounting to 1 to

[1] The Chilean pension system has obtained substantial attention in economics and finance research over the last decades due to its early adoption of personal retirement accounts. See, for example, Diamond and Valdés-Prieto (1994), Diamond (1996), Mitchell and Barreto (1997), Edwards (1998), Benartzi and Thaler (2001), Mitchell, Todd, and Bravo (2009), and Opazo, Raddatz, and Schmukler (2014) for a discussion of the Chilean experience.

5 billion US dollars and corresponding to 10% to 20% of funds' assets. A large aggregate price impact results as pension funds rebalance their portfolios worth billions of dollars within a few days. The price pressure in the equity market accumulates to 2.5% during the first eight days after the FyF recommendations and reverts subsequently. The cumulative price pressure is accompanied by abnormal turnover induced by the switches.

We find the largest price pressure on the day immediately following the FyF recommendations, possibly because smart investors front-run pension funds' trades. As the exact timing and amount of the fund switches is not predictable ex-ante, smart investors cannot completely anticipate pension funds' trades. This also explains why we observe price pressure after repeated events. Significant price pressure can be observed as late as eight days after the recommendation, especially when the recommendation generated large fund switches ex-post. This price pressure pattern is remarkably consistent with the prediction of DeLong, Shleifer, Summers, and Waldmann (1990b). Finally, placebo tests and additional robustness tests confirm that the price pressure is more likely to come from recommendation-based fund reallocations, rather than from other fundamental factors that triggered the recommendations in the first place.

The price pressure in the equity market is driven by relatively large stocks that dominate the pension funds' holdings. Smaller stocks, on the other hand, may not be traded as they are more illiquid and amount to a smaller proportion of the fund holdings. More generally, consistent with the findings in Greenwood and Thesmar (2011), the prediction in the cross-section is that stocks that receive higher pension portfolio weights (relative to their market cap) at the time of the recommendations would experience greater price pressure and excessive volatility. We show that this is the case using monthly panel regressions after controlling for other stock characteristics.

The price pressure in the government bond market is smaller although more persistent. The cumulative price impact reaches 30 basis points on average 12 days after the FyF recommendation date. The cumulative price impact is again accompanied by abnormal turnover and is more pronounced for long-term bonds. Cross-sectional regression analyses confirm these results.

Stambaugh (2014) documents that there has been a substantial decline in direct individual equity ownership in the U.S. Noise trading, which is driven primarily by individual investors, might become less pronounced as individuals reduce their direct stock ownership. However, the evidence in our paper suggests that noise traders can affect asset prices even when these assets are held primarily by large financial institutions. As Frazzini and Lamont (2008) argue, "it is hard for a fund manager to be smarter than his clients. Mutual fund holdings and performance are driven by both managerial choices in picking stocks and retail investor choices in picking managers." Such fund choices could be affected by "noise." For example, Da, Engelberg, and Gao (2014) show that an investor sentiment measure based on internet search results can predict daily mutual fund flows between equity and bond funds. As social media makes it easier to coordinate "noise trading," our results suggest that noise traders can still leave sizeable footprints in financial markets.

Our findings have important implications for the optimal design of pension systems. The literature on DC pension plans has documented that participants are often inert, follow default investment options, and are subject to behavioral biases.[2] Our paper documents that while there are good reasons for re-balancing retirement portfolios (e.g., life cycle dynamics, changes in risk tolerance, change in market environments) in a DC pension system, investors can also harm themselves and others if portfolio reallocations are too frequent. Indeed, as a response to these frequent fund switches, pension funds in Chile in the past two years have significantly reduced their holdings of less liquid securities and replaced them with cash. An increase in the proportion of highly liquid securities might not be optimal for retirement investors who typically have long-term investment horizons. This flexibility of investing in different funds could actually contribute to a classical limits of arbitrage argument (Shleifer and Vishny 1997), consistent with the insight from Stein (2005) on the open-ended fund structure design.

Our paper also speaks to the growing literature that studies the effects of financial advice on investor behavior.[3] While most of the literature has focused on the role of advisors in debiasing and improving financial decision making by individual investors via personal advice, we explore a market where financial advice seems to cater to investors' preferences and biases, more than an attempt to improve their financial decision making. Our paper also shows that financial advisors can impact aggregate returns and turnover by sending simultaneous advice to a large population of investors,

[2]Benartzi and Thaler (2001), Madrian and Shea (2001), Choi et al. (2002, 2004), Agnew, Balduzzi, and Sunden (2003), Huberman and Jiang (2006), Elton, Gruber, and Blake (2006, 2007), Brown, Liang, and Weisbenner (2007), Cohen and Schmidt (2009), Christoffersen and Simutin (2014), Sialm, Starks, and Zhang (2015), and Pool, Sialm, and Stefanescu (2015) discuss the structure of pension plans and the behavior of participants and administrators.

[3]See, for example, Lusardi and Mitchell (2007), Bergstresser, Chalmers, and Tufano (2009), Bhattacharya et al. (2012), Inderst and Ottaviani (2012a, 2012b), Mullainathan, Nöth, and Schoar (2012), Christoffersen, Evans, and Musto (2013), Chalmers and Reuter (2015), Foerster et al. (2015), Gennaioli, Shleifer, and Vishny (2015), and Von Gaudecker (2015).

which triggers coordinated portfolio switches and reallocations. This is possible by transmitting their advice through social media, a less explored channel in this literature. The impact of social media also explains why young investors seem to be more susceptible to this financial advice.

Our paper is also related to an extensive literature that has documented the impact of fund flows on fund returns. Edelen (1999), Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (2012) document persistent price pressure from fund flows. Whereas mutual funds flows are often driven by crises periods or by other extreme events, the frequent recommendation changes in Chile are less likely contaminated by fundamental determinants, offering us a cleaner setting to study price pressure. Chen, Goldstein, and Jiang (2010) provide empirical evidence that strategic complementarities among mutual fund investors generate fragility in financial markets. Our paper also suggests that participants in the Chilean pension system might have an incentive to switch their investment allocations if they expect other participants to switch based on the FyF recommendations.

Finally, our paper contributes to the emerging literature on media, investor attention and asset prices.[4] Since retail investors rarely short stocks, news grabbing their attention will on average lead to retail purchase and positive price pressure, as argued by Barber and Odean (2008). Our evidence suggests that retail attention can be coordinated via social media, and their correlated trading can lead to price pressure even at the market level. Retail attention can result in both positive and negative price pressure depending on whether it leads to inflows or outflows.

The rest of the paper is organized as follows. In Section 2, we give background information on the Chilean pension system and the FyF recommendations. In Section 3 we present the main price pressure results. Section 4 examines a typical investor's return to noise trading and its impact on return volatility. We conclude in Section 5.

[4] See Tetlock (2007), Cohen and Frazzini (2008), Corwin and Coughenour (2008), Fang and Peress (2009), Loughran and McDonald (2011), Da, Engelberg and Gao (2011), Engelberg and Parsons (2011), Gurun and Butler (2012), Peress (2014), and Peress and Schmidt (2014) among others.

2 Background Information

2.1 Chilean Pension Funds

The Chilean pension system was privatized in 1980 through the creation of a private DC pension fund system that substituted for the public pay-as-you-go system. By law all workers and employees have to contribute 10% of their taxable income to individual retirement accounts. This obligation to contribute does not apply to monthly incomes above a threshold of approximately US$3,000. Pension plan administrators (AFPs from their acronym in Spanish) charge a fee out of the contributions of the participants. Prior to 2008 they also charged a small maintenance fee per participant.

The pension fund industry has been instrumental to the development of the local financial market. Since 1980, AFPs have accumulated a sizeable portion of Chilean equity and fixed income assets. During the period from 2011 to 2013, the assets of the pension system amounted to around US$150 billion on average, which represented approximately 60% of Chilean GDP.

Since 2002, workers can choose between five types of funds that each AFP is legally bound to offer. These five funds (A through E) cater to different risk preferences of the plan participants. As reported in Panel A of Table 1, Fund A has the largest share of equities among the five funds and is considered to be the riskiest fund. Fund E is almost entirely invested in domestic fixed income securities. The largest fund is fund C, which accounts for close to 40% of the assets in the pension fund system. Fund C was the only available fund prior to 2002, which partially explains its relatively large size. Funds B, C, and D are default funds and participants are automatically shifted to less risky funds as they age. Funds A and E are not default options and are actively chosen by investors. Fund A accounts for approximately 20% of assets, similar to fund B, while funds D and E account for less than 15% and 10%, respectively.

The five types of funds are subject to different legal limits. For example, equity (domestic plus international) has to represent between 40% and 80% of fund A, between 25% and 60% of fund B, and so on. The relative order has to be preserved at all times (i.e., fund A has to invest more in equities than fund B, fund B more than fund C, etc.). This ensures that the investment becomes less risky as we move from fund A to fund E. There are also limits regarding to the fraction of foreign assets that pension funds are allowed to hold. Investors in funds A and B are more frequently young (under 30), investors in fund C are primarily middle-aged (between 30 and 55) and investors in funds D and E are more frequently older people (above 55). Interestingly, male investors are over-represented in the extreme portfolios which are actively selected.

The multi-fund system is designed to make it easy for investors to tailor retirement portfolios to their risk preferences. Indeed, investors can freely choose the fund to deposit their current and future contributions, as well as transfer the balances of their existing contributions between funds. Participants can submit a switching request on any day. Requests submitted before midnight are recorded on the corresponding day even if the switching requests were obtained after business hours. Once a switching request is submitted the change is effective four business days after the initial submission, a delay that was established for the pension fund managers to determine if the switching request contained clerical errors. The fund prices of a trade transaction are based on the prices on the second day after the initial fund-switching request was submitted by the participant. For example, a participant switching between funds A and E who owns one share of fund A will receive shares of fund E equal to the ratio of the prices between funds A and E on the second day after the switching request has been submitted.

In order to avoid large and abrupt changes, the regulator has established that funds cannot switch more than 5% of the fund shares on a single day. If the requested switches exceed that amount either for inflows or outflows, then the fund has to postpone the switches following a first-come first-serve rule until all switches have been executed. Thus, a 20% redemption request would delay the execution of late submitters by four days. Their transaction prices would be determined based on the market conditions on the sixth day after their switching request was submitted.

Our paper focuses on Chilean domestic equities and government bonds affected by the switches between funds A and E. Panel A of Table 1 documents that Fund A holds more domestic equity than fund E (16.9% vs. 1.1%, see Panel A) while fund E holds more domestic bonds than fund A (80.1% vs. 9.0%). Panel B of Table 1 gives a recent snapshot of fund A's holding of domestic equity and fund E's holding of government bonds. In terms of the composition of domestic equity portfolio, Panel B suggests that it is dominated by large stocks. For example, the largest ten stocks account for around half of the domestic equity portfolio. When pension fund managers have to trade fund A, they cannot avoid trading these large stocks while they could avoid trading smaller stocks that are in general less liquid.

The average time to maturity of the government bond portfolio is more than ten years, suggesting that Fund E holds a significant amount of long-term government bonds. Since long-term government bonds are mostly held by a few institutional investors (pension funds and insurance firms), it may be easier to locate the counter-party of a trade.

The pension fund industry is regulated by the Superintendencia de AFPs. (SAFP). The SAFP's mandate includes watching over investment limits, making sure that information is disclosed to investors, and other administrative tasks. Chilean law sets penalties for funds that perform poorly with respect to the average of their peers. This is implemented by establishing a minimum yield that is equal to the previous three-year return of the average fund in each risk profile less a few percentage points defined by law. Together with other forces that lead to herding among fund managers, such as competition and career concerns (Scharfstein and Stein, 1990), these penalties provide incentives not to deviate too much from the investment decisions of other pension fund managers (see Raddatz and Schmukler, 2013). In practice, penalties have never been imposed since 1998. Pension funds have to disclose their portfolios on a monthly basis, and the SAFP makes these portfolios available to the public on its website (www.safp.cl). This gives us a unique opportunity to see exactly what securities they hold at each point in time. We also collect data on prices, trading volume, and accounting variables (e.g., book value of equity) for domestic stocks from the Bolsa de Comercio de Santiago and Economatica.

2.2 Happy and Loaded

"Happy and Loaded" (or "Felices y Forrados" in Spanish, *FyF* in short) is an investment advisory firm that started their operations in 2011. They try to implement a simple market timing strategy using primarily funds A and E. They charge a relatively low fee (equivalent to roughly 6 US-cents per day). The information to clients is provided through e-mail and through their website. They warn subscribers when to switch between funds A and E. All users of FyF must have a username and password from their respective AFP so they can request the change as soon as they get the signal. FyF does not recommend different AFPs, they just make recommendations about the fund types. Table 2 provides a complete list of their recommendations up to March 2015. We focus on the first 15 recommendations that involve only funds A and E for most of our analysis, because the predictions are cleaner in this subset of recommendations.[5] If many investors follow their recommendations, we predict positive (negative) price pressure on bonds (stocks) when the recommendation is to move from A to E.

Figure 1 suggests that many investors follow the recommendations of FyF.[6] The time series of the daily number of individual change requests displays many spikes and these spikes can largely be associated with the recommendations from FyF immediately preceding them. This is especially true starting from the fifth recommendation when FyF began to attract investor attention by appearing on various social media.[7] The Google Search Volume Index (SVI) in Panel A of Figure 2 confirms this pattern. Investors only started to search "Felices y Forrados" after their fourth recommendation.[8] The subsequent 12 recommendations coincide with spikes in switching requests in Figure 1. Thus, starting in early 2012, FyF recommendations became a unique coordination device among pension investors.[9] Indeed, the last seven recommendations from FyF all triggered at least 10,000 individuals to switch between funds on the next few days.[10] Often, these switches will remain high for a few more days, potentially due to inertia or word of mouth effects as these recommendations get passed along from FyF subscribers to non-subscribers.

We also note that not all spikes in switching requests in Figure 1 are accompanied by FyF recommendations. The volatile equity market in 2008 prompted many investors to attempt to "time" the market. The fear of 2008 repeating itself prompted some investors to switch from fund A to E when there is a large drop in the equity market, explaining a few other spikes in fund switching requests. For example, the spikes in March 2011 and July and August 2011 were all preceded by a large drop in the Chilean equity index.

Figure 1 provided by the pension regulator plots the daily total number of fund switching

[5] We find similar results in robustness checks after including the more recent recommendations that represents partial switches. These partial switches receive smaller weights (as summarized in the last column of Table 2).

[6] This figure was provided to us by the Chilean pension regulator. We do not have access to the underlying data at the daily frequency.

[7] For example, the FyF LinkedIn profile was created on September 27, 2011 and the FyF Twitter account was created in January 2012. The oldest pictures on their Facebook page are dated March 2012.

[8] The spike in Google Search Volume in June 2013 is explained by a report published by the local regulator of pension funds (SAFP) against FyF.

[9] There exist other services similar to FyF, however they are significantly less well-known and have not achieved the notoriety of FyF, both in the news and in social media. Some other financial advisors that currently exist or existed during the years we study are Fondo Alerta (Fund Alert), Previsionarte and Tiempo Para Ganar (Time to Win).

[10] The FyF issue switching recommendation after the market closes. As a result, most actual switching requests are placed after the recommendation date.

requests, but does not break down the switches by fund types. Data on switching requests by fund types are only available at a monthly frequency and Panel B of Figure 2 plots the monthly number of switches from funds E to A (positive) and from A to E (negative). The plot confirms that the net fund switches are consistent with the recommendations issued by FyF.

While we cannot observe the exact formula used by FyF for making their recommendation, the analysis in Table 3 suggests that FyF follows a short-term trend-chasing strategy. We estimate two separate logit models to account for the two types of switches. In columns (1) to (3) (columns (4) to (6)), the dependent variable takes the value of one if a recommendation to switch to fund A (E) is issued that day, conditional on fund E (A) being the currently recommended fund. The explanatory variables are lagged stock and government bond returns, and fundamentals such as exchange rate changes, and inflation. The models are estimated with a penalized maximum likelihood estimator because of the low prevalence of the outcome. The pseudo R^2 is calculated following an analog of McFadden's pseudo R^2 ($1 - \frac{\ln Likelihood_{full}}{\ln Likelihood_{restricted}}$), where the full model is the specification presented in each column and the restricted model is the same specification with the constraint that all coefficients except the constant are equal to zero.

We find evidence that when the Chilean stock (government bond) market has experienced good returns during the most recent week, FyF is more likely to recommend switching from Fund E to A (A to E). In addition, exchange rate fluctuations are also helpful in explaining a switch to Fund E. The overall goodness of fit of the models in Table 3 (i.e., the Pseudo R^2) is low, however, suggesting that it is hard to explain FyF's recommendations with market data or fundamentals. Given their reliance on past returns one would not expect the FyF strategy to generate alpha when financial markets are at least weak-form efficient. Our subsequent analysis controls for these and other fundamental variables in examining future returns.

Another way to evaluate the informativeness of FyF recommendations is to investigate whether pension investors actually make money by following these recommendations. We examine this question by considering the following three investment strategies: (1) Buy-and-hold Fund A (Fund A); (2) Buy-and-hold Fund E (Fund E); (3) Switching between Fund A and E following FyF's recommendations immediately after receiving the recommendation (FyF). For strategy (3) we assume that the recommendation is sent out on day t, the switches will be made at the closing prices at day $t+2$ according to the rules. Since the recommendation is sent out after the market closes on day t, most investors will be requesting switches on or after day t (see Figure 1) and the switches will be made at prices on or after $t+2$, likely worse due to the price pressure we document. In addition, the execution of the transactions might be further delayed if the switching requests exceed 5%, as discussed previously. As such, the return to strategy (3) likely serves as an upper bound of the actual returns of an investor who follows FyF recommendations.

In addition, recall that there are six pension companies (AFPs) during our sample period, each offering funds A to E. As such, we first compute cumulative returns to the three strategies for each AFP and then average the returns across the six AFPs to obtain the average cumulative returns to following the three strategies. The returns on the same fund across different AFPs are very similar, again due to the minimum yield rule imposed by the regulator and the resulting herding investment behavior.

The average cumulative returns of the three strategies are plotted in Figure 3. The top panel shows the cumulative returns of investments of $1 in each strategy starting from the first FyF recommendation on July 27, 2011. This is the figure that will be prominently displayed in FyF's marketing material. Indeed, Figure 3 shows that FyF's "market timing" strategy outperforms both fund A and E by March 2014. The cumulative return is 15.8% for fund A, 21.0% for fund E, and 26.5% for FyF's market timing strategy. Furthermore, the FyF strategy almost always outperforms the other two passive strategies. It is not surprising that when facing such a performance track record, an average pension investor might be persuaded to follow FyF.

Nevertheless, returns in the top panel are misleading to an average pension investor since very few investors paid attention to FyF before January 2012, as documented on Figure 2. In addition, FyF only became popular because the first recommendations turned out to be very profitable. If we consider a "tradable" strategy where one starts the $1 investment from the fifth recommendation date on March 29, 2012, the FyF strategy underperforms both Funds A and E.

The above analysis suggests that the recommendations from FyF are unlikely to be informative. The correlated trading triggered by their recommendations is more likely reflecting noise trading rather than fundamental trading.

2.3 Evidence from Monthly Fund Flows

To obtain an idea of the magnitude of correlated trading we depict in Figure 4 the monthly net dollar flows of Funds A and E from 2003 when we first observe the monthly flow data. All numbers are converted to US dollars and measured in millions. Figure 4 shows very little switches between Funds A and E prior to 2008. We observe a flight-to-quality as investors pulled out money from Fund A and invested in Fund E during the financial crisis of 2008. As the market started to recover in 2009, we observe some flow reversals. The magnitude of these flows, however, is small compared to the large spikes after FyF became popular.

After 2011, we observe large flows to funds A and E that are almost mirror images of each other, coinciding with the FyF recommendations. These large flows are likely reflecting the coordinated noise trading triggered by FyF recommendations. Indeed, a FyF recommendation dummy can explain more than 27% of the variation in these flows post-2011 with a t-value of 3.24. The magnitude of the flows is often on the order of 1 to 5 billion US dollars. Recall from Table 1 that the sizes of funds A and E are only \$28 billion and \$14.1 billion, respectively. In other words, to implement the switches, the pension managers often have to trade 10% of their entire equity portfolio and 20% of their entire bond portfolio within a few days. Note that these monthly flows may potentially underestimate the correlated noise trading triggered by FyF's recommendation since FyF can make two recommendations in the same month. As consecutive switches are in opposite directions, their effects can offset each other and may not leave a large footprint in the monthly fund flow data.

These fund flows appear even larger when compared to the average turnover in the equity and government bond markets in Chile. For example, if funds trade their positions proportionally, then a 2,500 million fund flow implies the need to trade $2,500 \times (16.9\% - 1.1\%) = 395$ million worth of domestic equity.[11] For comparison, the daily turnover in the Chilean equity market amounts to only \$205 million. Likewise, a \$2,500 million fund flow implies the need to trade $2500 \times (80.1\% \times 38.2\% - 9.0\% \times 39.0\%) = \$677$ million worth of Chilean government bonds, much higher compared to the average daily turnover of \$130 million in Chilean government bonds. Not surprisingly, these trades, if forced to be implemented in a few days, can exert large price pressure.

[11] From Table 1 Panel A, 16.9% and 1.1% are the weights of Chilean stocks in funds A and E, respectively.

Younger investors might be more likely to be affected by FyF's recommendations given FyF's marketing strategy based on the internet and social media. One pension company called Modelo, has an investor base that is heavily tilted towards younger investors (see Table 4 Panel A). Most of Modelo's investors are young, because Modelo won in 2010 the first auction to allocate new labor market participants to pension fund providers. Young investors have to stay with Modelo for at least two years, and then they are free to move (other investors can choose Modelo too). We expect the flows to Modelo to be more sensitive to FyF's recommendations. In Panel B of Table 4 we regress the monthly flows to pension funds on dummy variables for months with a recommendation to switch between funds A and E. We then interact these dummy variables with an indicator variable for AFP Modelo. We control for lagged returns and flows of the same funds, plus AFP fixed effects.

We find that FyF recommendations to switch to fund A are associated with an average positive flow of 4.04% to fund A, while the flow to Modelo's fund A is further increased by 7.8%. The coefficients on the regression with flows to fund E are similar, but not necessarily of the same magnitude since funds A and E differ in size. Still, Modelo's fund E suffers larger outflows than other providers (7.19% higher) when FyF recommends switching towards fund A. FyF recommendations to switch to fund E are associated with an average outflow from fund A of 3.72%, while the outflow from Modelo's fund A is 10.46% higher. The recommendations to switch to E are associated with an average flow towards fund E of 16%, while the flow to Modelo is close to 5% higher (although not statistically significant). Overall, Modelo's flows are more volatile in months with FyF recommendations, as one would expect from a fund with a younger investor base.

3 Noise Trading and Price Pressure

So far, our evidence suggests that FyF recommendations, while containing little fundamental information, trigger large pension fund reallocations that reflect coordinated noise trading. These fund reallocations correspond to heavy trading volume, two to five times the average daily volume in both the equity and government bond markets. In this section, we focus on the price pressure generated by such trading activities.

3.1 Price Pressure in Event Studies

Figure 5 contains event-window plots of cumulative average returns and 90% confidence bands in both the equity and government bond markets after the FyF recommendations. Event day zero corresponds to the date when FyF sends out its switching recommendation. We consider an event window of 15 trading days since FyF can issue two opposite recommendations within the same month and their effects may net out if the event window is too long. We average cumulative returns across only the first 15 recommendations, which involve exclusively funds A and E (see Table 2). Finally, the equity market return is measured using Santiago's stock exchange main equity index (IPSA) and the government bond market return is measured using the "Dow Jones LATixx Chile Government Bond Index" which is a total return index. If the recommendation is to switch from Fund E to A, we use the raw cumulative equity and bond market return. If the recommendation is to switch from Fund A to E, we reverse the sign on the two returns. After this adjustment, stocks (government bonds) are predicted to receive positive (negative) price pressure after any email, so returns can be averaged across different recommendations to give an estimate of the average magnitude of the price pressure.

Figure 5 displays evidence for price pressure in the direction of FyF's recommendation. As seen from the top panel, the cumulative return accrues gradually in the equity market after the recommendation and eventually peaks at about 2.5% on day eight. Recall from Figure 1 that the spike in fund switches lasts for a few days after the recommendation. In addition, the pension managers have up to four days to implement the switches and can switch at most 5% of the fund on each day. As a result, the price pressure can persist after the event date. The eventual price reversal confirms that the initial price pressure is not driven by fundamentals or information. The cumulative price pressure is statistically significant on several days after the recommendations, as summarized in Table 5.

We see a consistent pattern in the government bond market. The price impact of trading is smaller in the government bond market but tends to be more persistent. The average cumulative return, which is negative, reaches -33 basis points on day 11. Unreported results demonstrate a complete reversal of the price pressure by day 80. One reason for the delayed reversal in the government bond market might be that these bonds (especially the long-term bonds held by the pension funds) are not traded very often, so the index potentially contains stale prices. Reallocation-induced trading results in an immediate price pressure but the reversal will not be observed until the next time these bonds are traded.

3.2 Placebo Tests

To ensure that these price pressure patterns are not driven by fundamentals in equity and bond markets that drive the FyF recommendation in the first place, we consider the following placebo test in Table 5. We select placebo dates during a similar 33-month period from July 2003 to March 2006, which coincides with the starting year of our data.

The placebo events are identified using a probit model where the dependent variable takes the value of one if the recommended fund is fund A and zero if it is fund E.[12] The explanatory variables in the probit model are lagged returns of stocks and government bonds, and fundamentals such as exchange rates changes, and inflation. The probit model is estimated in-sample during the period from July 2011 to March 2014 and we then compute the out-of-sample probability of FyF recommending fund A or E. Starting from a recommendation to hold fund A, we assume a change to fund E occurs whenever the probability goes below 25%. If fund E is being recommended, we assume a change to fund A occurs whenever the probability goes above 75%. We identify a total of 17 events in this period.

In contrast to the actual recommendation dates, in Table 5 we do not see any significant price pressure patterns in either the equity market or in the bond market when placebo dates with similar market conditions are used. In other words, the price pressure associated with the actual FyF recommendations is not driven by random chance, nor market conditions related to FyF recommendations.

3.3 Time-Series Regressions

The placebo test suggests that the price pressure we document is unlikely to be driven by market conditions that may trigger the FyF recommendations. To reinforce this point, we also control for past returns and other fundamental variables that can capture risk factors in time-series

[12] This is similar to Table 3, but with an unconditional model, because we cannot condition on the state of the recommendation out of sample.

regressions. The sample of daily returns covers the period between January 2010 and February 2014. The results are reported in Table 6. In these time-series regressions, we regress Chilean daily equity or bond index returns on event day dummies with and without a comprehensive set of controls. The "Day i" variables correspond to indicator variables that take the value of one if the day corresponds to the $i-th$ day after a recommendation was sent. Sell and buy recommendations are restricted to have the same impact. Thus, the indicator variable is one when recommending to buy equity and negative one when recommending to sell equity. Control variables include the cumulative returns in each of the four previous weeks, the sums of the squared returns in the same weeks, the lagged PE ratio, the lagged two- and ten-year government bond yields, lagged inflation, the percentage change in the exchange rate during the previous week, and the contemporaneous daily return of the MSCI Latam Index. The coefficient on each event day indicator variable thus isolates the magnitude of the "abnormal return" on that day.

We find a very consistent pattern regardless of whether control variables are included or not. For example, in column (2), we observe a large and significant price pressure in the equity market on day one of 64 basis points even after controlling for fundamental factors. Interestingly, the price pressure is not evenly distributed across event days. There is a large and significant price pressure on day one (64 basis points), a significant but smaller price pressure on day six (44 basis points), and another large and significant price pressure on day eight (55 basis points), followed by significant reversals on days nine and ten.

There are several reasons why the largest price pressure takes place on day one. As the FyF recommendations trigger an increasing number of fund switches over time, pensions funds no doubt became aware of them. Anticipating large fund switches in the near future triggered by a new recommendation, pension funds may choose to start trading already on day one rather than to wait until day four when these switches have to be implemented. In addition, investors anticipating the price pressure resulting from pension funds' trading may choose to "front-run" pension funds' trades. Since FyF recommendations are sent out after the market close on day zero, the earliest possible time they could trade is on day one. These front-running trades effectively shift the cumulative price pressure to earlier days. In the next few days, as these investors turn around and liquidate their positions, we do not necessarily observe significant price pressure on every single day. Smart investors do not completely front-run pension funds since there is uncertainty about the total magnitude of fund redemptions. Smart investors can also profit from liquidity provision by being the counterparties to pension funds' trades. The subsequent price reversals following the initial price pressure can therefore be interpreted as compensation for liquidity provision. Since short-selling is limited in Chile and there are no financial derivatives for hedging market risk, we expect liquidity provision to be more prevalent in the stock market when pension funds have to sell equity following an FyF recommendation to switch from Funds A to E. Evidence in Table 7 and unreported abnormal trading patterns by the direction of trading confirm this conjecture.

The fact that significant price pressure can be found as late as days six and eight can be explained by the regulatory limitation of fund redemptions to less than 5% per day. As seen from Figure 4, dollar flows resulting from these fund switches can be very large, often larger than 20% of Fund E's asset value. Since only 5% of the switches can take place each day, pension funds postpone their trades by as much as four days. Since both pension funds and smart investors are likely to be surprised by these largest fund switches, these residual trades that are forced beyond day six are less likely to be met by ready counterparties taking the other side of the trades, and therefore more likely to cause price pressure, followed by immediate price reversals.

Various subsample analyses reported in Table 7 provide supporting evidence for the price pressure hypothesis. Given the rule that funds cannot switch more than 5% of their net assets in one day, one would expect larger fund switches to take longer to implement and therefore the resulting price pressure to last longer. We test this idea by splitting our recommendations into two subsamples based on the percentage fund flow to Fund E during the recommendation month. The high-flow sample (column 1) consists of recommendations (1, 5, 9-15) during months when the Fund E flow exceeds 5% (in absolute term). The average absolute fund E flow across the high-flow months is 18.7%, which requires on average four days after day four to switch. Table 7 documents significant price pressure on days six and eight only among these high-flow months. In contrast, there is no significant price pressure beyond day one following remaining recommendations during the low-flow months (column 2).

We also split our sample based on the direction of switches. Recall that fund A is tilted towards equity while fund E holds almost only fixed income securities. When the recommendation is to switch from fund A to fund E, stocks have to be sold almost immediately in order to raise cash to transfer to fund E. On the other hand, when the recommendation is to switch from fund E to fund A, fund A could afford to hold the cash (received from fund E) for a while and more gradually purchase stocks. As such, one would expect larger price pressure in the equity market for recommendations to switch from fund A to E. This is exactly what we find when we compare the coefficients in column (3) to those in column (4).

Figures 1 and 2 suggest that FyF started to attract investor attention only from January 2012 when they appeared on the internet and various social media platforms. In other words, fund switches from the fifth recommendations are more likely to be triggered by FyF and reflect coordinated noise trading. Column 5 confirms that when we focus on recommendations 5 to 15, we obtain similar results.

So far, our analysis is focused on the first 15 recommendations which are homogenous in that they represent only switches between Funds A and E. Starting with their 16th recommendation on March 6, 2014, FyF began to recommend partial fund switches between Funds A, C, and E. In our final robustness check we include all 22 FyF recommendations. Since partial fund recommendations are predicted to trigger smaller amounts of trading, we underweight them in our analysis. The weights, reported in the last column of Table 2, are a function of the predicted trading volume. For example, a recommended switch from Fund E to an equal-weighted portfolio of Funds A and E receives a weight of 0.5 since only half of the Fund E needs to be replaced by equity. On the other hand, a recommended switch from Fund E to an equal-weighted portfolio of Funds C and E receives a weight of only 0.25 since Fund C is a balanced portfolio of equity and bonds, which further reduces the need for trading. The last column of Table 7 summarizes the results after including all 22 FyF recommendations. The inclusion of partial recommendations does not change our results in any significant way.

3.4 Price Pressure and Abnormal Trading in the Cross Section

Since pension funds' Chilean equity holdings are dominated by large stocks and government bond holdings are dominated by long-term bonds, the coordinated noise trading triggered by fund switches also has predictions in the cross-section. Specifically, we expect more noise trading and larger price pressure among larger stocks and longer-term bonds. Figure 6 confirms this hypothesis. Here, large stocks correspond to the ten largest stocks in the Santiago's stock exchange and small stocks correspond to the bottom forty stocks among the 50 largest stocks.[13] Long term bonds correspond to government bonds with maturities of ten years or longer and short term bonds are the remaining government bonds.

Coordinated noise trading suggests that large stocks and long-term bonds are traded more as the pension fund managers implement the switches between funds A and E. The left panels in Figure 6 confirm this conjecture. They plot the cumulative daily abnormal turnover in the equity and the government bond markets during the first 15 days after the FyF recommendation. Daily abnormal turnover is defined as the daily turnover minus the average daily turnover for each stock or bond between days $t-16$ and $t-6$ relative to the day each recommendation is made. Daily abnormal turnover is then accumulated from event day one, and it is value-weighted across stocks or bonds in each group. The top left panel shows that only large stocks experience heavier than usual trading for at least 11 days after the recommendation. The bottom left panel shows abnormal trading on long-term bonds only.

Heavier abnormal trading results in greater price pressure. The top right panel shows that while both large and small stocks experience price pressure that is reversed eventually, the pattern is more pronounced for larger stocks. The cumulative average return peaks at 2.5% for large stocks and only 1.3% for small stocks. Similarly the bottom right panel shows that long-term bonds experience stronger price pressure than short-term bonds. The price pressure is as large as 60 basis points for long-term bonds, compared to less than 20 basis points for short-term bonds.

Figure 6 shows differences between large and small stocks and between long-term and short-term bonds, in a way that supports the existence of coordinated noise trading. Tables 8 and 9 then confirm that these differences are statistically significant even after controlling for fundamental characteristics of these securities.

In Table 8, we examine the returns on different stocks and government bonds in panel regressions:

$$R_{it} = \sum_{j=1}^{10} \beta_j EventDay_j + \gamma Z_{it} + \varepsilon_{it}, \tag{1}$$

[13] Other stocks are sparsely traded. For instance, the IPSA index covers only 40 stocks. Even large stocks are not traded on some days (e.g., holding companies have large market capitalization, but are often illiquid). We treat returns as missing when a stock is not traded on the current or the previous day.

where R_{it} corresponds to the return of security i on date t (in calendar days); $EventDay_j$ is an indicator variable for an event day; and Z_i is a set of security characteristics. For stocks, the set includes size, book-to-market ratio, and momentum. For bonds, the set includes size, duration, coupon, and a dummy for nominal bonds. We also run an alternative test by focusing only on the differential effect between large (long) and small (short) stocks (bonds), while controlling for time fixed effects (δ_t). $Large_{it}$ is a dummy that identifies large stocks on each day:

$$R_{it} = \sum_{j=1}^{10} \beta_j (EventDay_j \times Large_{it}) + \gamma Z_{it} + \delta_t + \varepsilon_{it}. \tag{2}$$

In this equation, the time fixed effects absorb the event day dummies in Equation (1) that are not interacted. Consistent with Figure 6, we confirm in Table 8 that large stocks experience greater price pressure than small stocks. The difference between their returns is significant for several days. Likewise, long-term bonds experience significantly greater price pressure (in absolute term) than short-term bonds.

Table 9 repeats the panel regressions with turnover as the dependent variable. Event day indicator variables are set to one since turnover is always positive. The results confirm that large stocks and long-term bonds experience more abnormal trading than small stocks and short-term bonds.

Table 10 performs similar tests for the cross-section of stocks following the framework of Greenwood and Thesmar (2011) and Lou (2012). The intuition is that as pension fund managers scale up (down) their Chilean equity portfolios in order to implement the switches to (from) Fund A, stocks that are held relatively more by Fund A are more exposed to noise trading.

We measure *flow induced pressure* (FIP) as the value of the flow to Fund A on month t times the weight of stock i held in fund A's portfolio in month $t-1$ divided by the market cap of stock i in month $t-1$. We have portfolio data only at the end of each month, not at the daily level, and similarly for flows. Hence, emails on or after day 27 in a month are paired with flows from the following month. A stock with a higher FIP is predicted to be traded more and suffer a larger price pressure. We run regressions of cumulative returns over a given holding period, pooling all stocks across all events. For example, for cumulative returns on event day j:

$$R_{it}^{cum_j} = \lambda FIP_{it} + \gamma Z_{it} + \delta_t + \varepsilon_{it}. \tag{3}$$

In the previous regressions in Table 8 we use all dates during our sample period (January 2010-February 2014). Now we are using only those dates that correspond to day j in each event. The regression includes time-fixed effects because we pool across different dates for a particular event day. Panel A of Table 10 confirms that stocks with higher FIPs indeed suffer from larger price pressure following the FyF recommendations. The coefficients on FIP are always positive and are significant for days 2 and 3, even after controlling for stock characteristics such as size, book-to-market, and momentum. Panel B confirms the strong link between FIP and turnover. Stocks with higher absolute FIP are indeed traded more after the FyF recommendations. The coefficients on FIP are always positive and are significant after the third day.

The results so far paint a consistent picture: the FyF fund switching recommendations result in coordinated noise trading in both the equity and bond markets. This noise trading shows up in various measures of abnormal trading and coincides with large and significant price pressure in both markets, in the direction consistent with the FyF recommendation. Finally, the cross-sectional evidence suggests stronger effects among large stocks, stocks with high FIP, and long-term bonds, precisely the assets that are predicted to be traded more by the pension managers in order to implement the fund switches.

3.5 Noise Trading and Excessive Volatility

A long strand of literature starting from Shiller (1981) and Black (1986) suggests that noise trading can affect both the level and the volatility of asset prices. In this subsection, we take advantage of the cross-sectional variation in the stock market to study the impact of noise trading triggered by FyF recommendations on stock return volatility.

In Table 11, we regress monthly return volatility (computed from daily returns) on the FIP measure and on other controls including lagged volatility. The results confirm a strong link between predicted price pressure and return volatility. A 1% increase in the price pressure leads to a 0.71% increase in stock monthly volatility, even after controlling for other stock characteristics and past volatility.

3.6 Response from Pension Funds

Given our findings that fund switches can generate large price pressure and result in excessive volatility, it is natural to see how pension funds manage liquidity in response. The changes in their portfolio holdings over time plotted in Figure 7 reveal some interesting insights.

Specifically, we plot the portfolio weights of cash, ETFs, and Chilean equity for Fund A (left panel) and the portfolio weights of cash and Chilean fixed income securities for Fund E (right panel). The portfolio weights are computed using holdings reported at the end of each month and we aggregate these holdings across AFPs. The sample period starts in July 2011, coinciding with the first FyF recommendation and ends in December 2013.

Pension funds are holding more liquid assets in response to fund switches. As the fund switches became popular in mid-2012, both funds A and E started to hold more cash. In addition, fund A started to replace the less liquid Chilean stocks with more liquid ETFs. Fund E also decreased its holding of Chilean bonds.

In Table 4, we find that fund flows to the particular pension company Modelo are more sensitive to the FyF recommendations. Consequently, we expect Modelo's portfolio cash holdings to respond more to the recommendations and that Modelo may hold more cash on average to alleviate the impact from such a volatile fund flow. Table 12 examines the cash holdings of different AFPs in detail. Specifically, we regress monthly cash holdings (in percentage of total fund asset value) of different AFPs on indicator variables for FyF recommendations. The recommendation indicator variable is set equal to one during a month when the recommendation is a switch towards A; negative one when the recommendation is a switch towards E; and zero otherwise.

When we focus on Fund A, we find that while all AFPs increase their cash holdings over time, the increase is twice as large for Modelo. In addition, the positive coefficient on the recommendation variable suggests that Fund A experiences an increase (decrease) in cash holdings following a switch to Fund A (E). The response of Modelo's cash holdings to FyF recommendations is twice as large compared to the average AFP. When we focus on Fund E, we find similar patterns. Fund E experiences an increase (decrease) in cash holdings following a switch to Fund E (A) and this effect is slightly stronger for Modelo although less significant. One reason is that Modelo's Fund E holds significantly more cash from the very beginning (14.4% as evident in the constant coefficient and small coefficient on the time trend).

When we examine the cash holdings in Funds B, C, and D, we find a significant decrease over time, suggesting that AFPs are moving cash out of these three funds in order to deal with the flows in Funds A and E. Not surprisingly, the decrease in cash holding is also twice as large for Modelo.

The evidence in Figure 7 and Table 12 provides evidence that AFPs respond to the volatile fund flow triggered by FyF recommendations by holding more cash. While more liquid cash holdings help to buffer liquidity shocks, excessive cash holdings can be a performance drag and can hurt the long-term returns of retirement investors.

3.7 Welfare Costs

Following similar welfare cost calculation in Calvet, Campbell, and Sodini (2007), we consider a textbook asset allocation problem where a mean-variance investor allocates her investment between a risky portfolio and a risk free asset (cash). Her utility will be maximized at the optimal risky portfolio weight. Any deviation from that optimal weight will result in an utility loss equal to $0.5A\sigma^2 Dev^2$, where A, σ, and Dev denote the risk-aversion parameter, standard deviation on the risky portfolio and deviation from the optimal weight accordingly.[14]

Assume funds held optimal level of cash before the introduction of FyF in 2011, then increases in cash holdings (for Funds A and E) and decreases in cash holdings (for Funds B, C, and D) both lead to utility loss. Assume a risk aversion parameter $A = 5$ and risky portfolio monthly standard deviation $\sigma = 0.2$, then a 10% change in cash holding reduces utility by $0.5 \times 5 \times 0.2^2 \times 0.10^2 = 0.10\%$, equivalent to a 10 bps reduction in monthly risk-adjusted return.

Of course, utility loss from holding a sub-optimal portfolio represents only an indirect cost to pension investors. Increased turnover and the excessive holding of liquid assets are examples of more direct costs to pension investors, especially those investing in Funds A and E.

[14] Let ER and Rf denote the expected return on the risky portfolio and the risk free rate, then the optimal weight on the risky portfolio is $w^* = \frac{ER-Rf}{A\sigma^2}$. Utility as a function of the weight on risky portfolio is $U(w) = Rf + w(ER - Rf) - 0.5Aw^2\sigma^2$. Welfare loss can then calculated as $L = U(w^*) - U(w')$. After some algebra, it can be shown that $L = 0.5A\sigma^2(w^* - w')^2$.

4 Conclusion

Taking advantage of several features of the Chilean Pension system, we document a novel channel through which noise trading, if coordinated, can exert large price impact at aggregate level in both equity and bond markets even when these markets are dominated by institutional investors.

In Chile where pension assets account for 30% of free float in the stock market, pension investors often switch their entire pension investments from Fund A (holding mostly risky stocks) to Fund E (holding mostly riskfree government bonds), or vice versa, in an attempt to "time the market." After an investment advisory firm called "Felices y Forrados" (FyF) gained popularity in 2011 by providing fund switching recommendations, these signals served as a coordination device among individual noise traders. In order to implement the resulting fund switches, pension fund companies often have to trade 10% of their domestic equity and 20% of their bond portfolios within a few days. Not surprisingly, this coordinated noise trading leads to large price pressure of almost 2.5% in the equity market and more than 30 basis points even in the relatively liquid government bond market and to excessive volatility.

As a response to these frequent fund flows, pension funds in Chile have significantly reduced their holdings of less liquid securities and replaced them with cash. An increase in the proportion of highly liquid securities might not be optimal for retirement investors who typically have long-term investment horizons. One implication of our findings is that too much freedom in reallocating retirement portfolios may destabilize financial markets and impose social costs on retirement investors.

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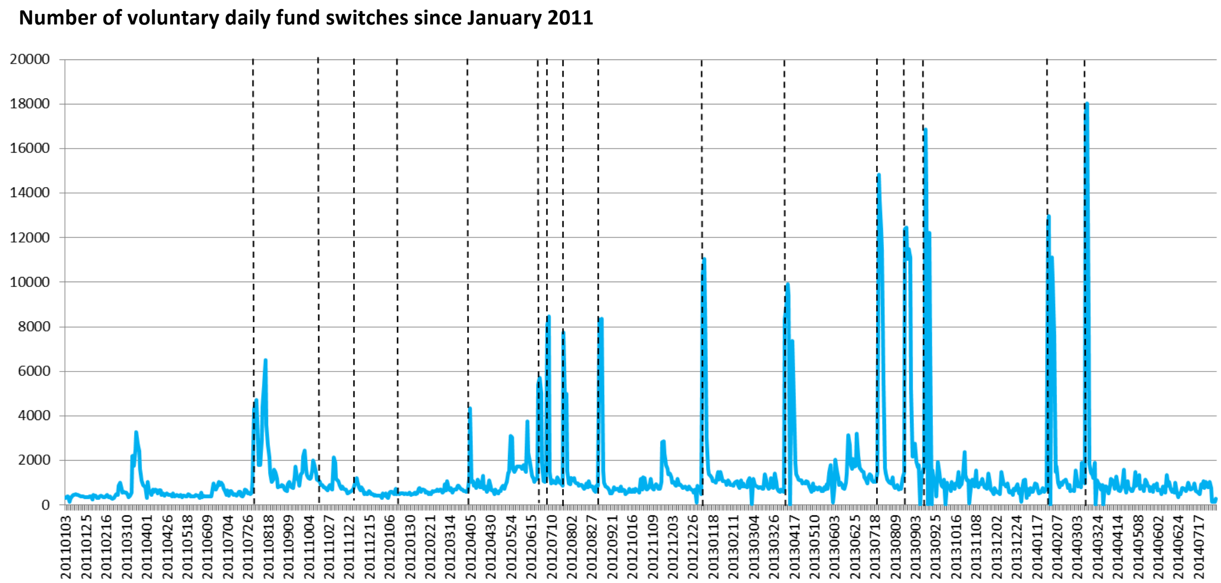
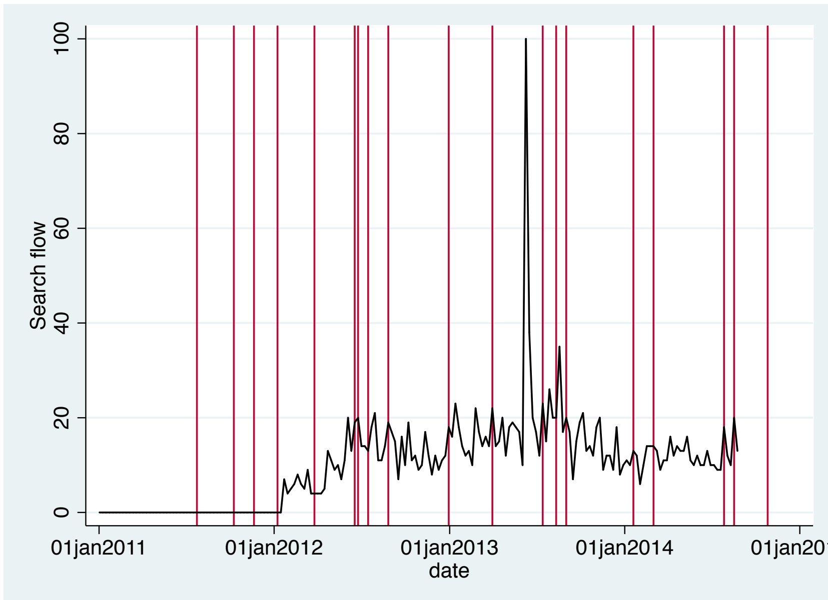


Source: Superintendencia de Pensiones, Chile.

Figure 1: Daily number of individual requesting change of fund to pension fund managers. Vertical lines mark the dates when FyF sent a switch recommendation. The data was provided by the Superintendencia de Pensiones using administrative records; vertical lines with dates were added by the authors.

(a) Panel A.



(b) Panel B.

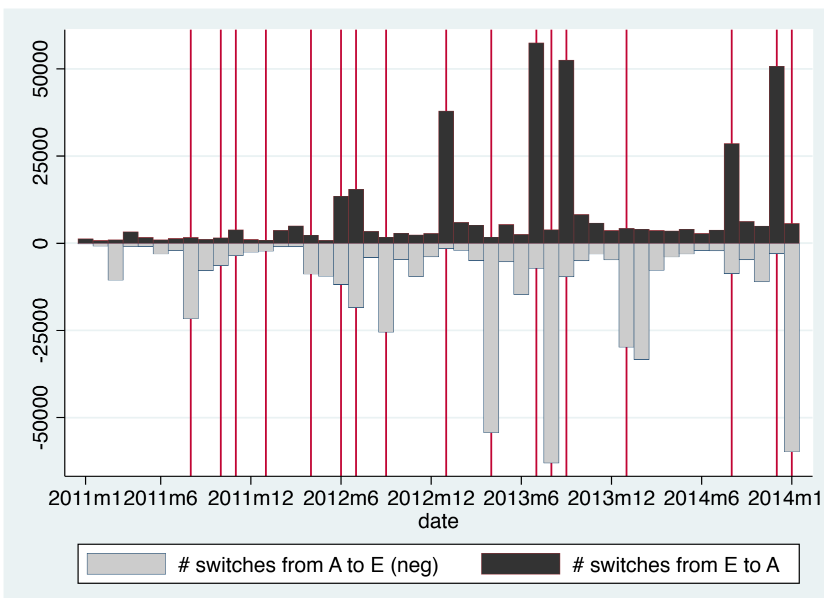


Figure 2: Panel A shows the weekly Google Search Volume Index (SVI) on "Felices y Forrados" since 2011. Panel B shows the total number of fund switches requested by affiliates of the system during a month, from fund E to A, and from fund A to E (shown as negative number). Vertical lines mark the switching recommendation by Felices y Forrados, adjusted so that a recommendation in the last three days of a month is marked in the following month.

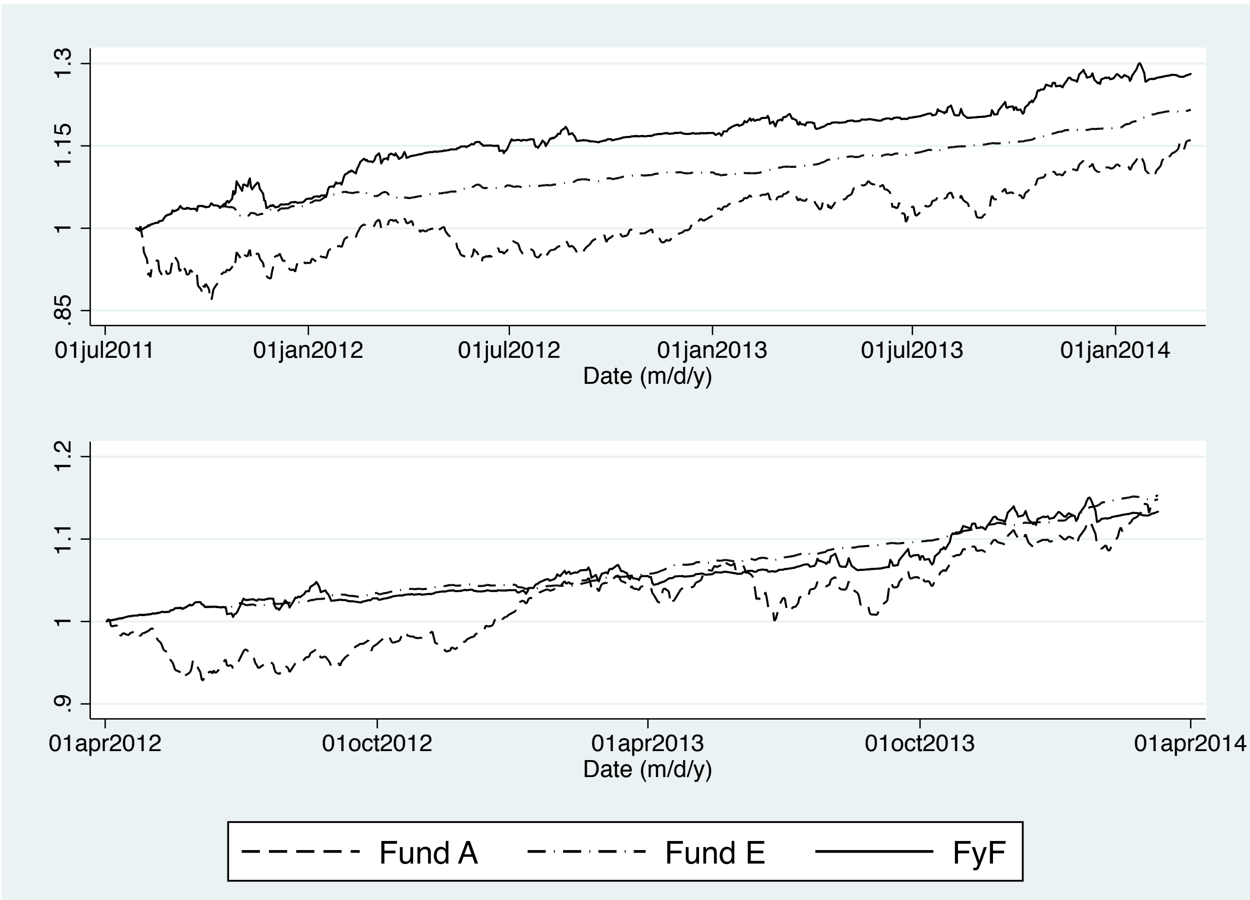


Figure 3: Cumulative returns to investment strategies. We compute the cumulative returns to following the following three investment strategies: (1) Buy-and-hold Fund A (Fund A); (2) Buy-and-hold Fund E (Fund E); (3) Switching between Fund A and E following FyF's recommendations immediately after receiving the recommendation (FyF). We consider two cases: we invest a dollar in each strategy starting from (1) the first FyF recommendation (Jul 27, 2011); (2) the fifth recommendation (Mar 29, 2012).

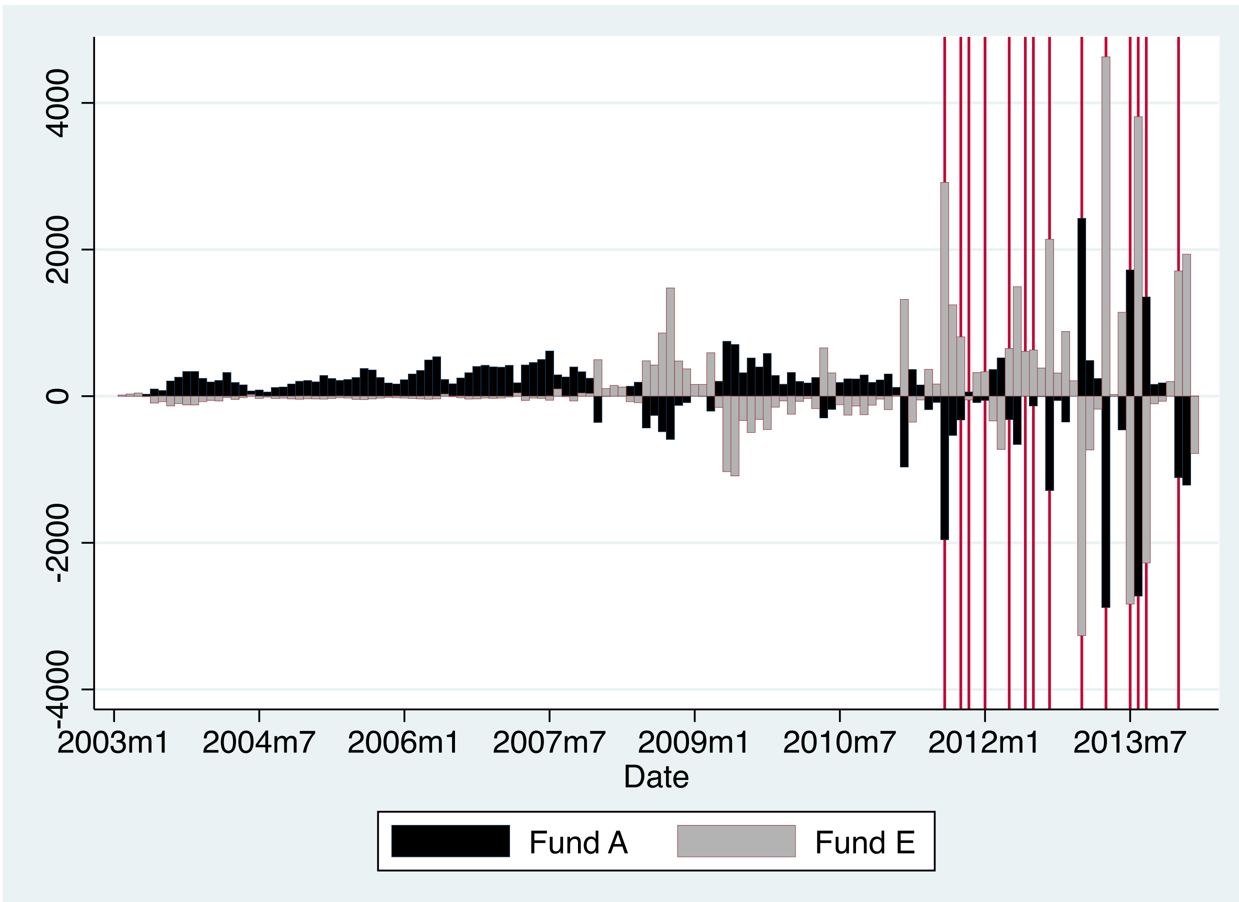


Figure 4: This figure shows the monthly dollar flows of funds A and E. We plot the aggregate dollar flows (in millions of USD) of the equity fund (A) and the fixed income fund (E). Positive and negative numbers indicate inflows and outflows, respectively. Vertical lines show the months when there was a switch recommendation by Felices y Forrados, adjusted so that a recommendation in the last three days of a month is marked in the following month.

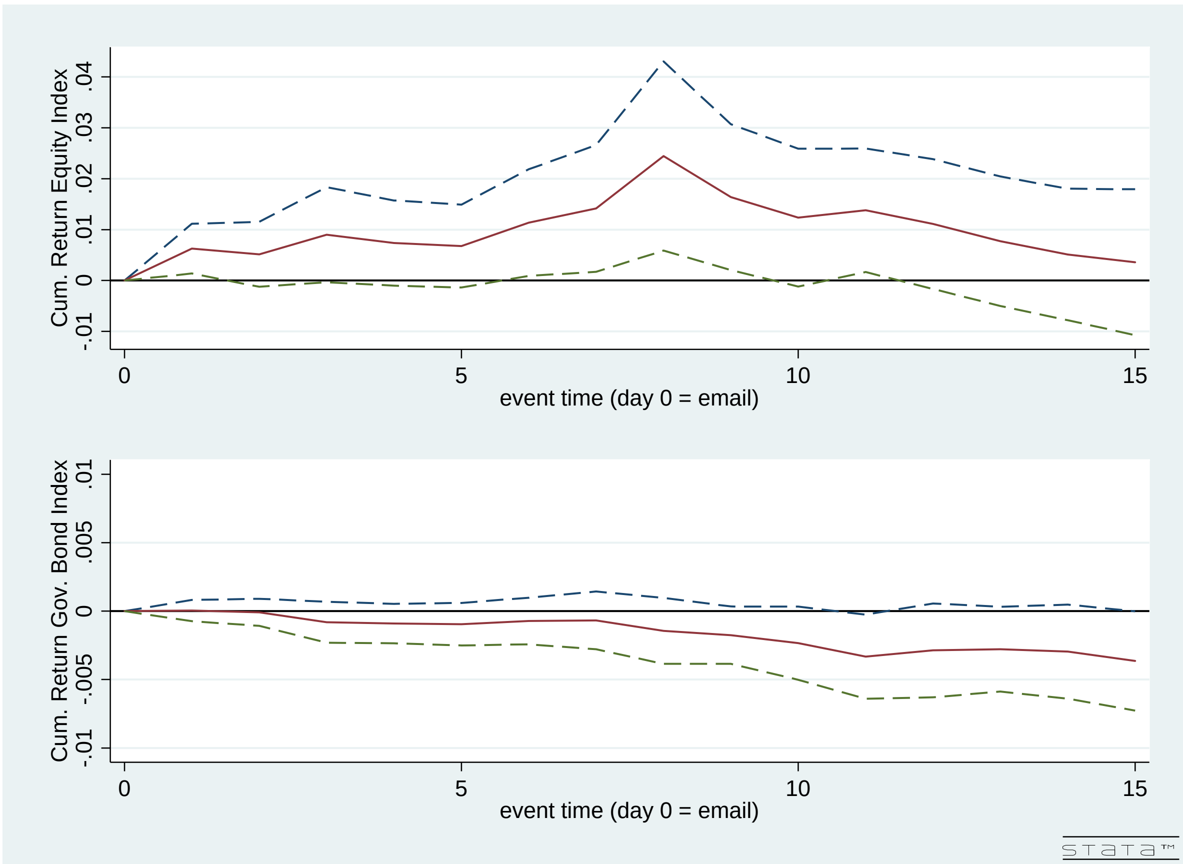


Figure 5: Cumulative average returns for the 15 recommendations. The top figure shows the results for Santiago's stock exchange equity index. The bottom figure corresponds to the government bond index, "Dow Jones LATixx Chile Government Bond Index" produced by LVA Indices. Day 0 is defined as the day when the recommendation is sent, which occurs after the market has closed. The solid line shows the simple average of the cumulative index returns for the 15 events on the corresponding event date. Dashed lines correspond to the 90% confidence intervals.

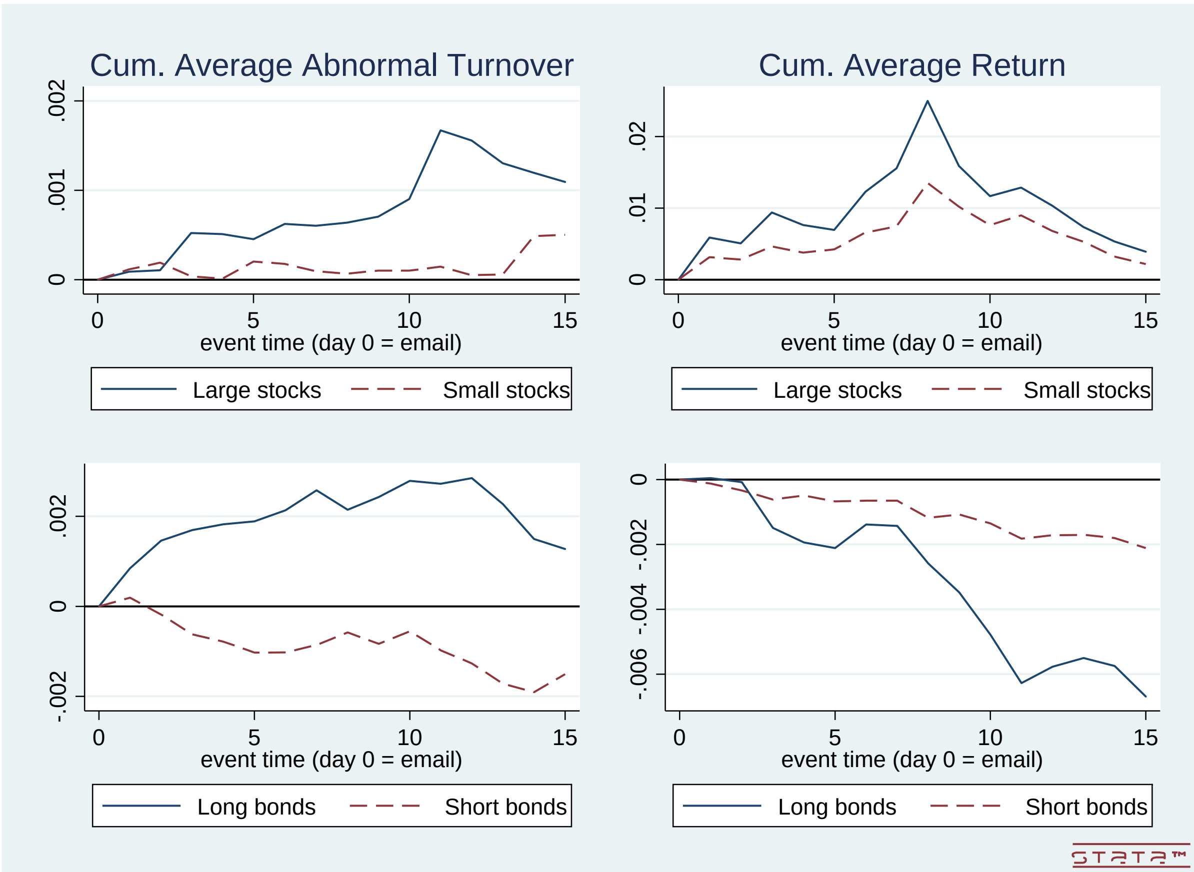


Figure 6: Cumulative abnormal turnover, leftmost column, and cumulative average returns, rightmost column, for the 15 recommendations for stocks separated by size and government bonds separated by maturity. Day 0 is defined as the day when the recommendation is sent, which occurs after the market has closed. Large stocks correspond to the ten largest stocks in Santiago's stock exchange, small stocks are the bottom forty stocks among the 50 largest stocks. Long bonds correspond to bonds with maturities of ten years or more, short bonds are the bonds with maturities shorter than ten years. Returns are raw (unadjusted) returns and turnover corresponds to abnormal turnover defined as turnover minus the average daily turnover for each stock or bond between days $t-16$ and $t-6$ from the day each recommendation is made.

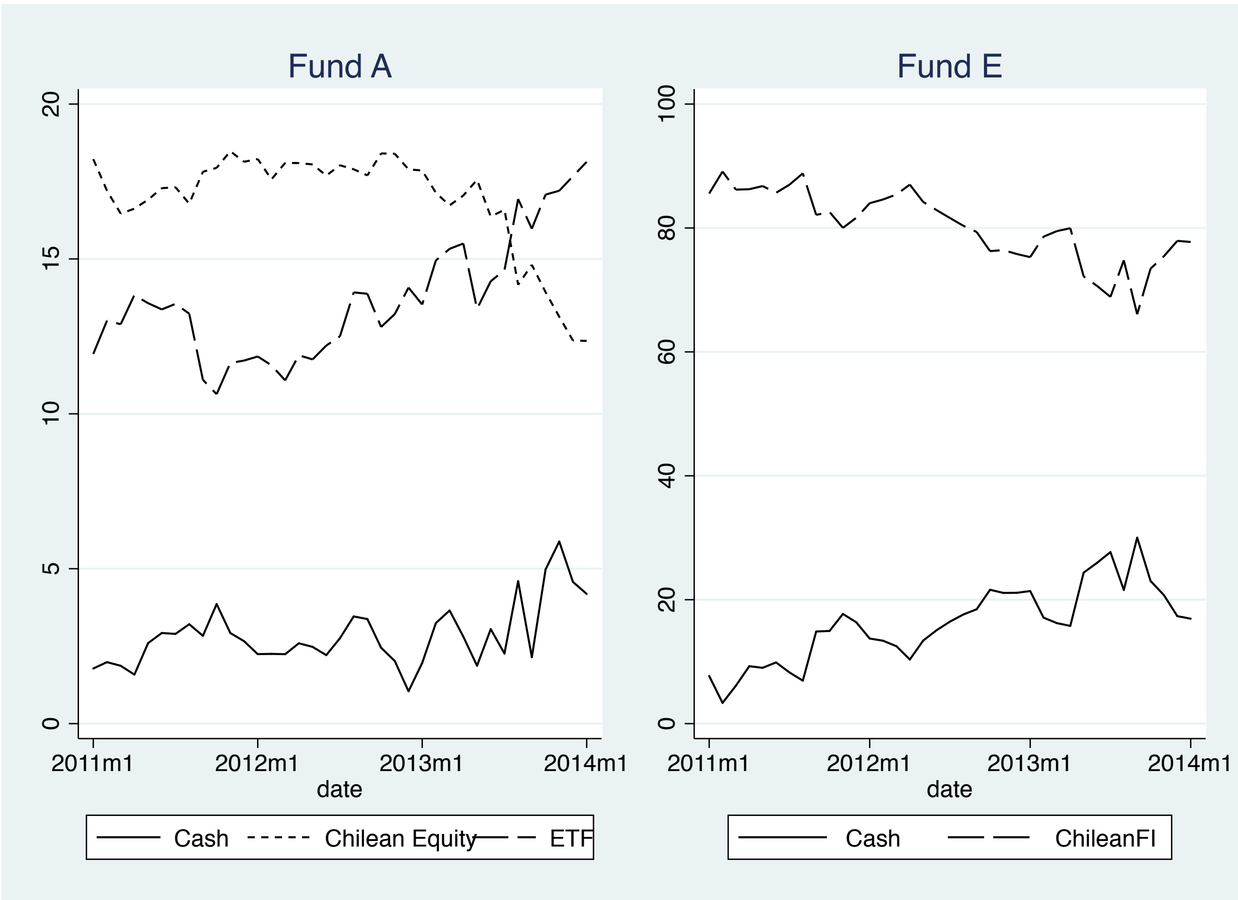


Figure 7: Portfolio holdings of Fund A and E over time. We plot the portfolio weights of cash, ETFs, and Chilean equity for Fund A (left); the portfolio weights of cash and Chilean fixed income securities for Fund E (right). The portfolio weights are computed using holdings reported at the end of each month and we aggregate these holdings across AFPs. The sample period starts in July 2011, coinciding with the first FyF recommendation and it ends in December 2013.

Table 1: Characteristics of five fund classes. Panel A reports the total asset values, portfolio compositions, and investor demographics of funds A to E. The indicator variables "young," "middle," and "old" correspond to investors under 30, between 30 and 55, and above 55, respectively. These characteristics are first aggregated across different AFPs each month, then averaged across time starting from 2011. Panel B reports the descriptive statistics of the portfolio composition of pension funds A and E and that of the market portfolio. Data corresponds to the pension system aggregates during the first six months of 2011. Data is taken from administrative records published by the Superintendencia de Pensiones.

Panel A

Fund	Fund A	Fund B	Fund C	Fund D	Fund E
Assets (billion USD)	28.0	27.9	60.6	22.4	14.1
Portfolio weights (%)					
Cash	2.9	4.9	4.9	9.6	16.4
Chilean fixed income	9.0	25.1	43.4	60.4	80.1
Chilean equity	16.9	17.4	13.8	6.6	1.1
International MF	52.0	39.6	26.6	16.5	0.4
ETF	13.7	7.8	5.6	3.7	0.9
CEF	4.5	4.1	4.1	2.0	0.0
Others	1.1	1.1	1.5	1.1	1.1
Demographics (%)					
Young	45.0	46.9	6.8	5.3	17.0
Middle	53.7	50.0	82.8	31.0	59.7
Old	1.3	3.2	10.4	63.6	23.3
Men	58.8	53.1	52.6	43.1	57.7

Panel B

	Fund A	Fund E	Market
Average % of Domestic Equity in largest 10 stocks	49.8	55.0	58.5
Average % of Domestic Equity in 2nd largest 10 stocks	26.4	24.4	20.7
Average % of Domestic Equity in 3rd largest 10 stocks	9.2	14.6	8.0
Average % of Domestic Equity in 4th largest 10 stocks	4.4	1.5	5.3
Average % of Domestic Equity in 5th largest 10 stocks	1.5	1.1	3.5
Average % of Domestic Equity in other stocks	8.6	3.9	4.1
Average % of Domestic Fixed Income in Government Bonds	39.0	38.2	37.7
Average Maturity Government Bonds (years)	10.0	11.0	8.7

Table 2: List of portfolio recommendations sent by FyF to their clients. Recommendations are made to subscribers after the market closes on the evening of the day in column "Date sent". For the first 15 recommendations the recommendations consider only strategies between equity (fund A) and fixed income (fund E).

Recommendation		Recommended change		Buying pressure on	Weight
Number	Date sent	From fund	To fund		
1	July 27, 2011	A	E	Bonds	-1
2	October 12, 2011	E	A	Equity	1
3	November 22, 2011	A	E	Bonds	-1
4	January 11, 2012	E	A	Equity	1
5	March 29, 2012	A	E	Bonds	-1
6	June 19, 2012	E	A	Equity	1
7	June 28, 2012	A	E	Bonds	-1
8	July 19, 2012	E	A	Equity	1
9	August 29, 2012	A	E	Bonds	-1
10	January 2, 2013	E	A	Equity	1
11	April 2, 2013	A	E	Bonds	-1
12	July 17, 2013	E	A	Equity	1
13	August 16, 2013	A	E	Bonds	-1
14	September 6, 2013	E	A	Equity	1
15	January 24, 2014	A	E	Bonds	-1
16	March 6, 2014	E	0.5C + 0.5E	Stocks	0.25
17	August 5, 2014	0.5C + 0.5E	E	Bonds	-0.25
18	August 19, 2014	E	0.5A+0.5E	Stocks	0.5
19	October 30, 2014	0.5A+0.5E	A	Stocks	0.5
20	December 15, 2014	A	E	Bonds	-1
21	February 12, 2015	E	0.5A+0.5E	Stocks	0.5
22	March 18, 2015	0.5A+0.5E	A	Stocks	0.5

Table 3: Determinants of FyF recommendations. We estimate two separate logit models. The first model, presented in columns 1 to 3, corresponds to a logit model where the dependent variable takes the value of one if a recommendation to switch to fund A is issued that day, conditional on fund E being the currently recommended fund. The second model, see columns 4 to 6, corresponds to a logit model where the dependent variable takes the value of one if a recommendation to switch to fund E is issued that day, conditional on fund A being the currently recommended fund. The explanatory variables in the logit model are lagged returns of stocks and government bonds, and fundamentals such as the exchange rates changes, and inflation. The models are estimated with a penalized maximum likelihood estimator because of the low prevalence of the outcome. We use daily data between email 1 and 16. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Fund E to Fund A			Fund A to Fund E		
	(1)	(2)	(3)	(4)	(5)	(6)
Chilean equity index return week -1	56.67***	104.40**	77.56*	−5.34	−5.19	−2.57
	(2.65)	(2.51)	(1.80)	(−0.30)	(−0.28)	(−0.12)
Chilean equity index return week -2	13.24	14.58	13.15	12.25	4.35	3.77
	(0.88)	(0.80)	(0.44)	(0.66)	(0.23)	(0.17)
Chilean equity index return week -3	19.59	63.06*	31.65	−23.10	−27.02	−16.09
	(1.27)	(1.83)	(0.75)	(−1.28)	(−1.38)	(−0.71)
Chilean equity index return week -4	0.78	72.24*	47.09	1.25	−2.89	−6.82
	(0.05)	(1.90)	(1.24)	(0.08)	(−0.16)	(−0.29)
Chilean gov index return week -1	14.43	47.06	77.54	219.20*	133.80	104.80
	(0.13)	(0.29)	(0.41)	(1.66)	(1.44)	(1.05)
Chilean gov index return week -2	−60.33	−137.40	−129.70	3.43	−11.82	−10.29
	(−0.55)	(−1.16)	(−1.08)	(0.04)	(−0.15)	(−0.12)
Chilean gov index return week -3	141.70	46.32	55.21	−41.00	−23.81	−37.24
	(0.95)	(0.37)	(0.41)	(−0.43)	(−0.27)	(−0.40)
Chilean gov index return week -4	−113.00	−159.40*	−156.30	−159.30**	−148.80*	−143.30
	(−1.11)	(−1.67)	(−1.43)	(−2.11)	(−1.92)	(−1.64)
Exchange rate change week -1		10.82	−3.32		54.22**	53.91*
		(0.22)	(−0.06)		(1.99)	(1.90)
Exchange rate change week -2		−39.86	−37.59		10.82	18.33
		(−0.90)	(−0.77)		(0.34)	(0.50)
Exchange rate change week -3		29.39	19.30		9.51	15.99
		(0.83)	(0.54)		(0.31)	(0.45)
Exchange rate change week -4		142.30***	115.10**		−6.23	−3.59
		(2.80)	(2.46)		(−0.27)	(−0.14)
Inflation		−51.92	−0.19		−54.38	−62.01
		(−0.42)	(−0.00)		(−0.35)	(−0.37)
MSCI Latam index return week -1			9.79			−1.36
			(0.37)			(−0.06)
MSCI Latam index return week -2			0.48			−3.12
			(0.02)			(−0.15)
MSCI Latam index return week -3			22.15			−22.68
			(0.75)			(−1.30)
MSCI Latam index return week -4			15.92			4.58
			(0.64)			(0.27)
N	352	336	336	441	441	441
Pseudo R^2	0.08	0.15	0.13	0.08	0.08	0.08

Table 4: Demographics and flows across pension companies. Panel A reports the fractions of young investors in Funds A and E across different pension companies (AFPs) in Chile. In Panel B, we regress monthly fund flows of different AFPs on FyF recommendation indicator variables and interaction terms. Although not reported, the regressions also include lagged fund flows and returns up to 6 lags. The regressions also include AFP fixed effects.

Panel A

	Percentage of Young Investors (below 35 yrs)	
AFP	Fund A	Fund E
MODELO	94%	53%
CAPITAL	63%	24%
CUPRUM	50%	19%
HABITAT	66%	27%
PLANVITAL	64%	40%
PROVIDA	69%	25%

Panel B

	Dependent Variable: Fund Flows (%)	
Variables	Fund A	Fund E
Switch towards A	0.040***	−0.019
	(0.014)	(0.032)
Switch towards A × Modelo AFP	0.078**	−0.072*
	(0.029)	(0.036)
Switch towards E	−0.037***	0.163***
	(0.010)	(0.041)
Switch towards E × Modelo AFP	−0.105***	0.053
	(0.037)	(0.043)
N	225	227
R^2	0.689	0.534

Table 5: Cumulative returns in the Chilean equity and bond markets around actual and placebo dates of FyF recommendations. We only consider the first 15 recommendations of FyF. Placebo dates are selected between July 2003 and March 2006. The "Day" column indicates the event time taking as day 0 the day when recommendation was sent, and this is done *after* the market has closed, in true events, and the counterfactual date for the placebo events. The placebo events were identified using a probit model where the dependent variable takes the value of one if the recommended fund is fund A and zero if it is fund E. The explanatory variables in the probit model are lagged returns of stocks and government bonds, and fundamentals such as the exchange rates changes, and inflation. The probit model is estimated in-sample during the period from 2011/07 to 2014/03 and we then compute the out-of-sample probability of FyF recommending fund A or E. Starting from a recommendation to hold fund A, we assumed a change to fund E occurs whenever the probability goes below 25%. If fund E is being recommended, we assume a change to fund A occurs whenever the probability goes above 75%. We identify a total of 17 events in this period. The equity index corresponds to the results using Santiago's stock exchange selective equity index (IPSA). The government bond index uses the "Dow Jones LATixx Chile Government Bond Index" produced by LVA Indices. For the actual events we average cumulative returns across the 15 recommendations, and for the placebo experiment we average across 17 placebo events found in the pre-FyF sample. Returns after recommendations to sell equity are multiplied by -1 before averaging across events. Standard errors are based on cross sectional t-tests.

	Actual Events					**Placebo Events**				
Day	Equity Index		Govt./ Bond Index		N	Equity Index		Govt./ Bond Index		N
	CAR	std.err.	CAR	std.err.		CAR	std.err.	CAR	std.err.	
1	0.0063*	0.0030	0.0000	0.0000	15	0.0001	0.0011	0.0000	0.0003	17
2	0.0052	0.0039	−0.0001	0.0007	15	0.0005	0.0026	−0.0006	0.0005	17
3	0.0090	0.0057	−0.0008	0.0009	15	−0.0022	0.0024	−0.0005	0.0005	17
4	0.0074	0.0051	−0.0009	0.0009	15	−0.0010	0.0023	−0.0009	0.0007	17
5	0.0068	0.0050	−0.0009	0.0009	15	−0.0003	0.0043	−0.0002	0.0007	17
6	0.0114*	0.0064	−0.0007	0.0010	15	−0.0023	0.0052	−0.0001	0.0011	17
7	0.0142*	0.0076	−0.0007	0.0013	15	−0.0031	0.0058	0.0002	0.0007	17
8	0.0245**	0.0113	−0.0014	0.0014	15	−0.0030	0.0070	0.0001	0.0009	17
9	0.0164*	0.0087	−0.0018	0.0013	15	−0.0029	0.0073	−0.0002	0.0009	17
10	0.0123	0.0082	−0.0023	0.0016	15	−0.0058	0.0069	−0.0007	0.0011	17
11	0.0138*	0.0073	−0.0033*	0.0018	15	−0.0053	0.0076	−0.0005	0.0013	17
12	0.0111	0.0077	−0.0029	0.0021	15	−0.0068	0.0072	−0.0004	0.0012	17
13	0.0077	0.0077	−0.0028	0.0019	15	−0.0055	0.0082	−0.0006	0.0015	17
14	0.0051	0.0078	−0.0030	0.0021	15	−0.0010	0.0100	−0.0004	0.0013	17
15	0.0036	0.0088	−0.0036	0.0022	15	−0.0020	0.0095	−0.0002	0.0014	17

Table 6: Time-series regressions of daily returns for Chilean equity and government bonds, from January 2010 to February 2014. The equity return is the return of Santiago's stock exchange selective equity index (IPSA). The government bond return is the return of the "Dow Jones LATixx Chile Government Bond Index" produced by LVA Indices. "Day i" variables correspond to indicator variables that take the value of one if the day corresponds to the $i-th$ day after a recommendation was sent. Sell and buy recommendations are restricted to have the same impact in absolute value. Day indicator variables are a positive one when recommending to buy equity and a negative one when recommending to sell equity. Control variables include the cumulative returns in each of the four previous weeks, the sums of the squared returns in the same weeks, the lagged PE ratio, the lagged 2- and 10-yr government bond yields, lagged inflation, the percentage change in the exchange rate the previous week, and the contemporaneous daily return of the MSCI Latam Index. PE is taken from Bloomberg and corresponds to the value reported 30 trading days earlier. Lagged inflation is measured as the inflation rate of the month corresponding to 30 trading days earlier. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	Equity return		Gov bond return	
	(1)	(2)	(3)	(4)
Day 1	0.0078***	0.0064***	−0.0002	0.0000
	(0.003)	(0.002)	(0.000)	(0.000)
Day 2	−0.0009	0.0008	−0.0003	−0.0003
	(0.003)	(0.002)	(0.000)	(0.000)
Day 3	0.0041	0.0033	−0.0008**	−0.0006
	(0.003)	(0.002)	(0.000)	(0.000)
Day 4	−0.0016	−0.0011	−0.0001	−0.0000
	(0.002)	(0.002)	(0.000)	(0.000)
Day 5	−0.0006	−0.0021	−0.0000	0.0001
	(0.002)	(0.002)	(0.000)	(0.000)
Day 6	0.0046*	0.0044**	0.0002	0.0002
	(0.002)	(0.002)	(0.000)	(0.000)
Day 7	0.0028	0.0009	0.0000	0.0001
	(0.002)	(0.002)	(0.000)	(0.000)
Day 8	0.0103***	0.0055***	−0.0008*	−0.0004
	(0.002)	(0.002)	(0.000)	(0.000)
Day 9	−0.0081***	−0.0045**	−0.0003	−0.0006
	(0.002)	(0.002)	(0.000)	(0.000)
Day 10	−0.0040*	−0.0047**	−0.0006	−0.0005
	(0.002)	(0.002)	(0.000)	(0.000)
Controls	no	yes	no	yes
N	1,038	997	1,038	997
R^2	0.046	0.358	0.011	0.102

Table 7: Time-series regressions of daily returns for Chilean equity, from January 2010 to February 2014. The dependent variable in all panels is the return of Santiago's stock exchange selective equity index (IPSA). In columns (1) and (2) we separate the recommendations into those that generated high (recommendations 1, 5, and 9 to 15) and low monthly flows (recommendations 2, 3, 4, and 6 to 8). The next two columns, (3) and (4), we separate the sample according to the direction of the recommended switch. In column (5) we include only the recommendations that were sent after the website had been officially launched (i.e., from recommendation 5). In column (6) we include in our estimation all the recommendations that recommended partial switches between funds A, C and E (starting with recommendation 16 in Table 2). "Day i" variables correspond to indicator variables that take the value of one if the day corresponds to the $i-th$ day after an recommendation was sent. Sell and buy recommendations are restricted to have the same impact in absolute value (Day dummies are a positive one when recommending to buy equity and a negative one when recommending to sell equity). Control variables include the cumulative returns in each of the four previous weeks, the sums of the squared returns in the same weeks, the lagged PE ratio, the lagged 2- and 10-yr government bond yields, lagged inflation, the percentage change in the exchange rate the previous week, and the contemporaneous daily return of the MSCI Latam Index. PE is taken from Bloomberg and corresponds to the value reported 30 trading days earlier. Lagged inflation is measured as the inflation rate of the month corresponding to 30 trading days earlier. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	High flow	Low flow	Sell equity	Buy equity	Internet presence	Expanded sample
	(1)	(2)	(3)	(4)	(5)	(6)
Day 1	0.0058**	0.0073**	0.0054*	0.0068**	0.0073***	0.0035*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 2	0.0019	−0.0018	0.0039	−0.0030	0.0007	−0.0003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 3	0.0035	0.0027	0.0054*	0.0006	0.0042*	0.0037**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 4	−0.0004	−0.0026	0.0000	−0.0024	−0.0026	−0.0011
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 5	−0.0002	−0.0047	−0.0008	−0.0037	−0.0037	0.0003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 6	0.0057**	0.0021	0.0064**	0.0020	0.0039*	0.0024
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 7	0.0005	0.0018	0.0029	−0.0018	−0.0008	0.0011
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 8	0.0106***	−0.0014	0.0075***	0.0032	0.0046**	0.0051***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 9	−0.0064**	−0.0015	−0.0043	−0.0055*	−0.0026	−0.0062***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Day 10	−0.0068***	−0.0015	−0.0063**	−0.0035	−0.0039*	−0.0030*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Controls	yes	yes	yes	yes	yes	yes
N	917	862	893	884	937	1,326
R^2	0.358	0.303	0.354	0.302	0.308	0.361

Table 8: Panel regressions of daily returns for Chilean stocks and government bonds, from January 2010 to February 2014. "Day i" variables correspond to indicator variables that take the value of one if the day corresponds to the $i-th$ day after an recommendation was sent. Sell and buy recommendations are restricted to have the same impact in absolute value Day dummies are a positive one when recommending to buy equity and a negative one when recommending to sell equity. Columns labeled "Stock returns" correspond to panel regressions of returns of the 50 largest stocks in the Chilean market. Large stocks are the ten largest stocks in Santiago's stock market, small stocks are the other 40 stocks among the 50 largest. The column "Large-Small" is a regression of all stocks pooled together, on a full set of date fixed effects and the interactions between the event day dummies and a dummy for large stocks. We report the coefficients only for these interactions. The columns labeled "Bond returns" correspond to panel regressions of (ex-coupon) returns of government bonds (indexed 2, 5, 7, 10, 20, and 30 years, and nominal 2, 5, 7, and 10 years). Long bonds are the bonds with maturity equal or longer than 10 years, short bonds are those with maturity of less than 10 years. The column "Long-Short" is analogous to the "Large-Small" column. All regressions for stocks include as controls size, book-to-market ratio and momentum. All regressions for bonds include as controls size, duration, coupon, and a dummy for nominal bonds. Standard errors are clustered by day and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	Stock returns			Bond returns		
	Large	Small	Large-Small	Long	Short	Long-Short
Day 1	0.0081***	0.0059***	0.0026	−0.0003	−0.0002	−0.0001
	(0.0025)	(0.0018)	(0.0016)	(0.0007)	(0.0004)	(0.0004)
Day 2	0.0080***	0.0063***	0.0017	−0.0005	−0.0003	−0.0003
	(0.0029)	(0.0017)	(0.0021)	(0.0005)	(0.0002)	(0.0003)
Day 3	−0.0011	−0.0003	−0.0005	−0.0013*	−0.0003	−0.0010*
	(0.0020)	(0.0016)	(0.0013)	(0.0008)	(0.0003)	(0.0006)
Day 4	0.0071***	0.0029*	0.0044***	−0.0005	0.0002	−0.0007
	(0.0025)	(0.0015)	(0.0014)	(0.0006)	(0.0002)	(0.0004)
Day 5	−0.0019	−0.0005	−0.0014	−0.0005	−0.0003	−0.0002
	(0.0029)	(0.0020)	(0.0014)	(0.0004)	(0.0002)	(0.0003)
Day 6	0.0008	0.0016	−0.0011	0.0005	0.0000	0.0005
	(0.0036)	(0.0026)	(0.0018)	(0.0007)	(0.0003)	(0.0006)
Day 7	0.0040	0.0013	0.0028**	0.0000	−0.0001	0.0001
	(0.0028)	(0.0022)	(0.0013)	(0.0006)	(0.0003)	(0.0004)
Day 8	0.0070	0.0044	0.0022*	−0.0013*	−0.0006*	−0.0007*
	(0.0049)	(0.0040)	(0.0012)	(0.0007)	(0.0004)	(0.0004)
Day 9	0.0002	0.0011	−0.0007	−0.0006	0.0001	−0.0007
	(0.0059)	(0.0031)	(0.0029)	(0.0006)	(0.0002)	(0.0004)
Day 10	−0.0069***	−0.0025*	−0.0042**	−0.0013**	−0.0003	−0.0010**
	(0.0026)	(0.0015)	(0.0019)	(0.0006)	(0.0003)	(0.0004)
Fixed effects	no	no	time	no	no	time
N	9,233	28,331	37,564	3,976	5,964	9,940
R^2	0.0206	0.0064	0.2288	0.0089	0.0075	0.4356

Table 9: Panel regressions of daily turnover for Chilean stocks and government bonds, from January 2010 to February 2014. Turnover is defined as traded volume divided by amount outstanding, an it is winsorized at the 0.1% level. "Day i" variables correspond to indicator variables that take the value of one if the day corresponds to the $i-th$ day after an recommendation was sent. Day dummies are a positive one when recommending to buy equity and a negative one when recommending to sell equity. Columns labeled "Stock turnover" correspond to panel regressions of turnover of the 50 largest stocks in the Chilean market. Large stocks are the ten largest stocks in Santiago's stock market, small stocks are the other 40 stocks among the 50 largest. The column "Large-Small" is a regression of all stocks pooled together, on a full set of date fixed effects and the interactions between the event day dummies and a dummy for large stocks. We report the coefficients only for these interactions. Columns labeled "Bond turnover" correspond to panel regressions of turnover of 10 government bonds (indexed 2, 5, 7, 10, 20, and 30 years, and nominal 2, 5, 7, and 10 years). Long bonds are the bonds with maturity equal or longer than 10 years, short bonds are those with maturity of less than 10 years. The column "Long-Short" is analogous to the "Large-Small" column. All regressions for stocks include as controls size, book-to-market ratio and momentum. All regressions for bonds include as controls size, duration, coupon, and a dummy for nominal bonds. Standard errors are clustered by day and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	Stock turnover			Bond turnover		
	Large	Small	Large-Small	Long	Short	Long-Short
Day 1	0.0118	−0.0040	0.0240***	0.2022**	0.0599*	0.3104***
	(0.0134)	(0.0090)	(0.0092)	(0.0797)	(0.0358)	(0.0904)
Day 2	0.0135	0.0068	0.0144	0.1246	0.0141	0.2785*
	(0.0109)	(0.0107)	(0.0121)	(0.1336)	(0.0300)	(0.1472)
Day 3	0.0027	−0.0049	0.0160	0.1403*	0.0184	0.2909***
	(0.0070)	(0.0115)	(0.0112)	(0.0832)	(0.0316)	(0.1073)
Day 4	0.0332	−0.0283***	0.0695	0.0941	0.0548*	0.1976**
	(0.0467)	(0.0054)	(0.0490)	(0.0626)	(0.0299)	(0.0781)
Day 5	0.0116	−0.0108**	0.0280**	0.0586	0.0293	0.1877***
	(0.0142)	(0.0052)	(0.0134)	(0.0556)	(0.0357)	(0.0659)
Day 6	0.0018	0.0028	0.0046	0.0576	0.0534	0.1634
	(0.0102)	(0.0109)	(0.0123)	(0.0856)	(0.0587)	(0.1184)
Day 7	0.0351	−0.0141*	0.0561**	0.1367	0.0844*	0.2120**
	(0.0261)	(0.0078)	(0.0241)	(0.0925)	(0.0459)	(0.0864)
Day 8	0.0001	−0.0171*	0.0233***	−0.0094	0.1007*	0.0500
	(0.0093)	(0.0087)	(0.0074)	(0.0787)	(0.0603)	(0.0811)
Day 9	0.0139	−0.0120*	0.0329***	0.0998	0.0298	0.2319**
	(0.0157)	(0.0071)	(0.0126)	(0.1031)	(0.0387)	(0.1102)
Day 10	0.0040	−0.0090**	0.0198**	0.1277	0.0817	0.2085**
	(0.0074)	(0.0041)	(0.0086)	(0.1139)	(0.0771)	(0.0898)
Fixed effects	no	no	time	no	no	time
N	8,994	27,920	36,914	3,687	5,964	9,651
R^2	0.0692	0.0116	0.0551	0.3567	0.1783	0.3480

Table 10: Regressions of cumulative returns and turnover on FIP. In each event day (from day one up to day ten), pooling across events, we run a regression of the cumulative return (turnover) on stock characteristics. FIP is the flow induced pressure measured as the flow received by the aggregate fund A in the pension fund system times the weight of each stock in fund A's portfolio in the previous month, and over the market capitalization of the stock in the previous month. We use the raw FIP for Panel A and the absolute value of FIP for Panel B. Other controls include size (log of market cap), the book-to-market ratio, and momentum. All regressions include event fixed effects. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Panel A. Dependent variable: cumulative return to day #									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FIP	0.839	1.870*	3.399**	2.297	1.017	1.449	1.128	2.465	1.237	1.369
	(0.815)	(1.134)	(1.440)	(1.605)	(1.870)	(2.008)	(2.135)	(2.398)	(2.578)	(2.649)
ln Mkt cap	0.001	−0.001	−0.001	−0.001	−0.002	−0.003*	−0.004*	−0.003	−0.002	−0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
B/M	0.000	−0.003	−0.003	−0.003	−0.002	−0.003	−0.004	−0.003	−0.003	−0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
MOM	−0.005	−0.005	−0.002	−0.002	−0.001	0.002	0.011	0.006	0.020*	0.019*
	(0.003)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)	(0.010)	(0.011)
N	471	472	471	471	471	469	469	469	469	469
R^2	0.355	0.288	0.315	0.225	0.214	0.356	0.421	0.599	0.425	0.353

	Panel B. Dependent variable: cumulative turnover to day #									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FIP (abs value)	0.063	0.154	0.616	0.844**	0.905*	1.191**	1.376**	1.632***	1.732***	1.935***
	(0.255)	(0.324)	(0.392)	(0.415)	(0.500)	(0.562)	(0.593)	(0.624)	(0.655)	(0.713)
ln Mkt cap	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
B/M	−0.000	−0.000	−0.001**	−0.002***	−0.002***	−0.003***	−0.003***	−0.004***	−0.004***	−0.004***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MOM	−0.000	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
N	471	472	471	471	471	469	469	469	469	469
R^2	0.033	0.043	0.054	0.062	0.063	0.068	0.071	0.082	0.087	0.089

Table 11: Excess volatility. The dependent variable is the monthly return volatility of the stocks in the sample. FIP is defined as the absolute value of the flow to Fund A in month t times the weight of stock i held in fund A's portfolio in month $t-1$ divided by the market capitalization of stock i. Momentum is the cumulated return between months $t-12$ and $t-2$. Market cap is the log of the market value of the stocks in Santiago's stock exchange measured on June of each year. B/M is book to market ratio measured in December of the previous year. Turnover corresponds to the average turnover of the past 12 months. Standard errors are clustered by month, and regressions include stock fixed effects and time fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
FIP (abs value)	1.506***	1.798***	0.773**	0.613*
	(0.368)	(0.407)	(0.292)	(0.359)
ln Mkt cap		−0.000	−0.000	−0.002*
		(0.000)	(0.000)	(0.001)
B/M		−0.001***	−0.000	−0.001
		(0.000)	(0.000)	(0.001)
MOM		0.002**	0.001	−0.001
		(0.001)	(0.001)	(0.001)
Turnover			0.043***	0.011
			(0.015)	(0.019)
Ret vol t-1			0.476***	0.206***
			(0.036)	(0.044)
Fixed effects	time	time	time	time stock
N	1,755	1,688	1,687	1,687
R^2	0.224	0.256	0.452	0.554
Number of cross-sections	48	48	48	48

Table 12: Monthly cash holding regression. We regress monthly cash holdings (in percentage of total fund asset value) of different AFPs on FyF recommendation indicator variables. The recommendation dummy is one during a month when the recommendation is a switch towards A; negative one when the recommendation is a switch towards E; and zero otherwise. Although not reported, the regressions in columns corresponding to "All AFPs" include AFP fixed effects.

	Fund A		Fund E		Funds B/C/D	
	All AFPs	Modelo	All AFPs	Modelo	All AFPs	Modelo
Intercept	2.091***	1.224**	7.562***	14.404***	8.203***	11.474***
	‘(0.434)	(0.637)	‘(2.312)	‘(2.189)	(0.430)	(1.163)
trend	0.043**	0.094***	0.477***	0.023	-0.092***	-0.177***
	(0.018)	‘(0.030)	(0.141)	(0.102)	(0.017)	(0.055)
Email	0.497**	0.971*	‘-0.827**	-1.000	-0.089	-0.099
	‘(0.255)	(0.540)	(0.422)	(1.851)	(0.171)	(0.994)
N	216	36	216	36	648	108
R2	0.105	0.298	0.357	0.010	0.050	0.091