Price Pressure from Coordinated Noise Trading: Evidence from Pension Fund Reallocations^{*}

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Abstract

We document a novel channel through which coordinated noise trading can exert large price impact at the aggregate level in both equity and bond markets. In Chile, pension investors often switch their entire pension investments between funds holding mostly risky stocks to funds holding mostly risk-free government bonds in an attempt to "time the market." These frequent portfolio reallocations are coordinated across individual investors by an investment advisory firm that has recently gained substantial popularity on social media. In order to implement the resulting fund switches, pension fund companies often face redemption requests amounting to 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.

(Key Word: Coordinated Noise Trading, Pension Funds, Price Pressure)

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1 Introduction

The impact of noise traders on asset prices is central to the debate over market efficiency. Black (1986) in his AFA presidential address points out that noise might cause market inefficiencies. De Long, 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 interesting features of the Chilean pension system, we provide a novel example where individual noise traders, if coordinated, can exert large price pressure in both equity and bond markets, even when asset ownership is dominated by institutions.

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.¹ It is a fully funded system run by private sector pension funds (AFP from their acronym in Spanish). Currently, 70% of Chilean workers contribute 10% of their salary to the system. As a result, the pension plans are substantial, holding assets worth USD 150 billions, almost 60% of the GDP. Close to 30% of the Chilean stock market free float and 30% of the Chilean government bond market are held through the pension system. In 2002, a multi-fund system was created where all AFPs offer five funds to investors, ranging from fund A holding mostly risky stocks to fund E holding mostly risk-free government bonds. The multi-fund system is designed to make it easy for investors to tailor their investments to their risk preferences. Indeed, investors can freely choose the fund to deposit their current and future contributions, as well as transfer the balance of their existing contributions between funds, all at almost no cost.² Many investors attempt to "time" the market where they switch their entire investments from fund A to E if they think the stock market will underperform the bond market in the near future, or vice versa.

An investment advisory firm called "Felices y Forrados" (FyF hereafter; the translation would

¹See, for example, Diamond and Veldes-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.

 $^{^{2}}$ The multi-fund pension system and the freedom for investors to switch between funds are not features unique to Chile. As of 2010, at least eight other countries (including Mexico, Peru, and Hungary) are using a similar system.

be "Happy and Filthy Rich") started in 2011 to cater to the popular demand for market timing. For a small fee of about US\$20 per year, FyF sends investors their switching recommendations (fund A to E or E to A) by e-mail or private website login. Their first recommendation to switch from fund A to E issued on July 27, 2011 proved to be hugely successful. Those who followed their advice avoided the 7% drop in the equity market during the subsequent week. Eventually, this success turned out to be nothing but beginner's luck. Their subsequent switching recommendations are mostly uninformative. Nevertheless, due to its initial success and an aggressive marketing campaign on social media, FyF gained popularity among Chilean Pension investors. As a result, email recommendations from FyF serve as a coordination device among noise traders. This is clearly evident in Figure 1: the spikes in the number of account switches closely coincide with the FyF email recommendations. The impact on the recommendations has increased over time as FyF was gaining popularity. Our analysis also suggests that young investors are more likely to follow FyF's recommendations.

These account switches involve large fund flows The flows to funds A and E are almost mirror images during the months of FyF recommendations. The flows amount to between 1 and 5 billion US dollars, which corresponds to as much as 20% of the funds' asset values.

Not surprisingly, as pension funds try to trade a significant fraction of their portfolios in a few days, a large price impact will be generated. Indeed, we find that the cumulative price pressure in the equity market is 2.5% on average and peaks on the eighth day after the FyF recommendation date before it reverts. 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. The price effect is especially pronounced in the more recent sample when the recommendations are more widely followed, possibly because smart investors start to front-run pension funds' trades. As the exact amount of the fund switches is not predictable ex-ante, smart investors cannot perfectly front-run pension funds' trades. Indeed, significant price pressure can be observed as late as eight days after the recommendation, especially when the recommendation generates large fund switches. The delayed price pressure is also attributable to a rule that requires pension funds to switch no more than 5% of the fund asset each day. As a result, an actual fund switch that represents 25% of fund E's assets may take several days to implement. This price pressure pattern is remarkably

consistent with the prediction of De Long, Shleifer, Summers and Waldmann (1990b). Placebo tests and additional robustness checks confirm that the price pressure is more likely to come from recommendation-triggered fund switches, rather than from other fundamental factors that might have triggered the recommendation in the first place.

In addition, the price pressure in the equity market is driven by large stocks that dominate the pension funds' holding. These are stocks AFPs have to trade to implement the fund switches. Smaller stocks, on the other hand, may not be traded as frequently as they are more illiquid. 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 switch will be traded more and experience greater price pressure. Such a price pressure, combined with the subsequent price reversal, results in excessive volatility.

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 accompanied by abnormal turnover and is more pronounced for long-term bonds with a maturity greater than or equal to 10 years. Cross-sectional regression analyses confirm these results.

The evidence in our paper suggests that noise traders can affect asset prices even when these assets are held directly 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 actually 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 sizable footprints in the financial market.

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 factors. 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.

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 is sent at the same time to a large group of investors affiliated to a mandatory savings system for retirement, and how that triggers coordinated portfolio switches and rebalancing. Our paper shows that financial advisors can also impact aggregate returns and turnover if their advice is widely disseminated.

Finally, our findings have implications for the optimal design of pension system. The literature on defined contribution (DC) pension plans has documented that participants are often inert, follow default investment options, and are subject to behavioral biases.⁴ Our paper documents that the design of a DC pension plan can create incentives by participants to reallocate their assets that can harm long-term retirement investors. Indeed, as a response to these frequent fund switches, AFPs in Chile in the past two years have significantly reduced their holdings of less liquid equity and debt securities and replaced them with cash. In addition, the frequent fund switches make Chilean pensions funds less willing to invest in illiquid assets even though they might be particularly beneficial for long-term retirement investors. Thus, the flexibility of rebalance across different funds could actually limit arbitrages, as suggested by Stein (2005) in the context of openended fund structures .

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.

³See Inderst and Ottaviani (2014) and the references therein.

⁴Benartzi 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 (2014), and Pool, Sialm, and Stefanescu (2014) discuss the structure of DC pension plans and the behavior of participants and administrators.

2 Background Information

2.1 Chilean Pension Funds

The Chilean pension system was privatized in 1980 through the creation of a private defined contribution pension fund industry that substituted the old pay-as-you-go system ran by the government. By law 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 fund administrators (AFPs from their acronym in Spanish) charge a fee out of the contributions of the workers, but since 2008 they do not charge maintenance fees for the fund (before 2008 the maintenance fee was a small fixed amount per worker).

The pension fund industry has been instrumental for the development of the local financial market. Since 1980, AFPs have accumulated a sizeable portion of Chilean equity and fixed income. For example, as reported in Table 1, during the period from 2011 to 2013, the assets of the pension system were close to US\$150 billion on average, which represents approximately 60% of Chilean GDP. Their holdings of domestic equity represented about 9% of the local market capitalization, and almost 30% of free float.

Since 2002, workers can choose from five types of funds that each AFP is legally bound to offer. These five funds (A through E) cover the different risk profiles of investors. As reported in Table 1 Panel A, 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. The largest type of fund is fund C, which accounts for close to 40% of the assets in the pension fund system during our sample period. Fund C was the only fund offered before 2002, hence its size. 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 guarantees that as you are moving from fund A to D, the investment becomes less risky. Not surprisingly, we find investors in funds A and B are primarily young people (under 30); investors in fund C are primarily middle-aged (between

30 and 55) and investors in fund D are mostly older people (above 55). Interestingly, as you are moving from fund A to D, we observe less male investors. Finally, there are limits regarding to the fraction of foreign assets (equities, fixed income, or any other non-Chilean asset) that pension funds hold.

The multi-fund system is designed to make it easy for investors to tailor their investments 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 at almost no cost.

The portfolio change requests are executed using a first-come first-serve rule. Any request submitted before midnight is recorded on this day even if it is done after business hours (as it is the case of requests submitted by the internet). If the total fund flows on a specific date amount to less than 5% of the fund assets, then the changes are effective four business days after the initial submission, a delay that was established for the pension fund managers to determine if the switch requests were legitimate. On the fourth business day the switches are recorded using the value of the fund two business days earlier, or the second day after the initial fund-switching requests were submitted by the participants. Thus, the flow between funds is effective on day four, but at day-two prices. For example, a participant switching between funds A and E will receive for each share of fund A shares of fund E equal to the ratio of prices between funds A and E on the second day. In order to avoid large and abrupt changes to the funds the regulator has established that a single fund cannot switch more than 5% of the fund in a single date. If the requested flows on a given day exceed that amount either for inflows or outflows, then each day the funds switches at most 5% following a first-come first-serve rule for the requests until all switches have been made. The execution delays on high-flow-dates also affects the pricing dates, which are determined based on prices two days prior to the effective switching dates.

A few interesting issues arise from these rules. First, passive investors may win or lose with the switches depending on the relative return between days t=2 and t=4 (or later) of the origin and destination funds. Unlike investors, the difference in the timing does not directly affect the pension fund managers. Their focus is on the long-run return of the fund and therefore their reputation of able managers. In fact, trying to game the system in favor of, say, passive investors who stay in their funds may make the situation worse: aggressive trading to deter switchers may increase the

price impact of the switches beyond what is manageable in the short run, and increase transaction costs. It is worth noting that Chilean regulation requires that pension fund administrators and not investors cover any direct transaction costs (fees and commissions).

Our paper focuses on Chilean domestic equities and government bonds affected by the switches between funds A and E. Seen from Panel A of Table 1, fund A holds more domestic equity than fund E does (16.9% vs. 1.1%, see Panel A) but fund E holds more domestic bonds than fund A does (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 10 stocks account for 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 more illiquid. When we compare the pension fund portfolio weights on the 50 largest stocks to the corresponding weights of the market portfolio, we find the pension funds to underweigh the largest 10 stocks, overweigh the middle 20 stocks, and underweigh the smallest 20 stocks. Nevertheless, on a relative scale, pension funds are underweighing the 10 largest stocks (big stocks) less than the 10 smallest stocks (small stocks).

We also find the average time to maturity of the government bond portfolio is more than 10 years, suggesting that fund E holds a significant amount of long-term government bonds. Indeed, the pension funds hold more long-term bonds than the market does.

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 3-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. The SAFP also requires that foreign stocks cannot be held directly and have to be held through mutual funds.

2.2 Investment Advisory Firm

The Chilean investment advisory firm "Happy and Filthy Rich" (or "Felices y Forrados" in Spanish, FyF in short) started operations in 2011. The firm trys to implement a simple market timing strategy using the funds offered in the Chilean pension system. They charge a low fee (equivalent to around US\$20 per year). Their recommendations to clients are provided via email and online on the private pages using a "traffic light"-style system. They warn people when to switch between the various funds. All users of FyF must have an username and a 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 funds. Table 2 provides a complete list of their recommendations up to November 2014. Due to the availability of the holdings data, we focus on the first 15 recommendations, we would predict positive (negative) price pressure on bonds (stocks) when the recommendation is to move from fund A to fund E.

Figure 1 provided by the pension regulator suggests that many investors follow the recommendations of FyF. The time series of the daily number of individual change requests display many spikes and these spikes can largely be explained by the email recommendations from FyF immediately preceding them. As FyF is gaining popularity over time, its recommendations are more likely prompting fund switches. Indeed, the last eight recommendations from FyF all triggered at least 10,000 individuals to switch between funds A and E on the next day.⁵ 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.

On July 27, 2011, FyF issued their first recommendation to switch from fund A to E. This recommendation turned out to be very successful. Those who followed this advice avoided the 7%

⁵The FyF usually issues switching recommendation after the market closes. As a result, most actual switching requests are placed after the recommendation date.

drop in the equity market during the subsequent week. Eventually, this success turned out to be nothing but beginner's luck. The subsequent switching recommendations are mostly uninformative. But thanks to this beginner's luck and the very aggressive marketing campaign including a constant presence in the news and social media, FyF gained high popularity within a year and their recommendations were associated with larger spikes in fund switches. In other words, starting in early 2012, FyF recommendation became an unique coordination device among noise traders. There are other services similar to FyF, however they are significantly less infuential and have not achieved the media presence that FyF has, both in the news and in social media.⁶

While we cannot observe the exact formula used by FyF for making their recommendations, our analyzes suggest that FyF follows a short-term trend-chasing strategy. Table 3 presents an ordered probit model where the dependent variable takes the value of one in days with an email recommending a switch towards fund A, zero in days without emails, and minus one in days with an email recommending a switch towards fund E. The explanatory variables in the ordered probit model are lagged returns and fundamentals such as the price-earnings ratio, bond yields, and the rate of inflation. We find that when the local stock market or the Latin American (Latam) index have experienced good (poor) returns over the past week, FyF tends to recommends switching from fund E to A (A to E). The strongest of the predictors is related to the exchange rate between Chilean pesos and the US dollar. If the peso has appreciated over the past week, then FyF is more likely to recommend switching to fund A. The exchange rate is the only predictor that survives in the specification including all control variables (column 4), although with a statistical significance of only 10%. The overall goodness of fit of the models in Table 3 (see pseudo R2) is low, indicating that it is hard to rationalize FyF's recommendations with market data or fundamentals. Given FyF's reliance on past returns one would not expect the FyF strategy to generate alpha if financial markets are at least efficient in the weak form.

⁶Some 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).

3 Correlated Noise Trading and Price Pressure

3.1 Evidence from Monthly Fund Flows

To obtain an impression of the size of the correlated noise trading, we plot in Figure 2 the monthly net dollar flows of funds A and E starting in 2003, when we first observe the flow data. All numbers are converted to US dollars and measured in millions. The figure shows very little switches between funds A and E prior to 2008. During the great recession of 2008 investors pull money from fund A and invest in fund E. As the market starts to recover in 2009, we observe some reversals. The magnitude of these flows, however, is small compared to the large spikes after 2011 as FyF becomes more popular.

We observe after 2011 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, just a FyF recommendation indicator variable can explain more than 27% of the variation in these fund flows post-2011 with a *t*-value of 3.24. The magnitude of the flows is often in the order of 1 to 5 billion US dollars. Recall from Table 1 that the average size of funds A and E amount to 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 recommended switches are in opposite directions, their effects can offset each other and may not leave a large footprint on 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, a 2.5 billion fund flow implies the need to trade $2.5 \times (16.9\% - 1.1\%) = 0.395$ billion worth of domestic equity.⁷ For comparison, the daily turnover in the Chilean equity market is only \$205 million. Likewise, a \$2.5 billion fund flow implies the need to trade $2.5 \times (80.1\% \times 38.2\% - 9.0\% \times 39.0\%) = 0.677 billion worth of Chilean government bonds, compared to the average daily turnover in the Chilean government bond market of \$130 millions. Not surprisingly, these trades, if forced to be implemented in a few days, can exert large

⁷From Table 1 Panel A, 16.9% and 1.1% are the weights of Chilean stocks in funds A and E, respectively.

price pressure.

3.2 Price Pressure from Event Studies

Figure 3 contains event-window plots of cumulative average returns in both the equity and government bond markets. Event day 0 corresponds to the date when FyF sends out its switching recommendation. The equity market return is measured using Santiago's stock exchange equity index. 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; otherwise, we change the signs on these two returns. After this adjustment, stocks (government bonds) are always predicted to receive positive (negative) price pressure so these cumulative returns can be averaged across different recommendations to give an estimate of the average magnitude of the price pressure. We consider the first 15 recommendations which only involve funds A and E (see Table 2). Finally, 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.

Figure 3 provides evidence for price pressure in the direction of FyF's recommendation. As seen from the top panel, the cumulative returns accrue gradually in the equity market after the recommendation and eventually peak at about 2.5% on day eight. Recall from Figure 1 that the increase 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 for a while after the event date. The eventual price reversal confirms that the initial price pressure is not driven by information.

We observe a similar pattern in the government bond market. Since government bonds are more liquid, the magnitude of the price pressure is smaller. The average cumulative return, which is negative, reaches 30 basis points after 11 days before leveling out. Governments bonds in Chile are traded over the counter and additional search frictions may arise, which may explain why the price pressure is more persistent and does not revert within 15 days.

The regression results in Table 4 confirm the event-window plots in Figure 3 and suggest that the price pressure on domestic bond and equity securities is statistically significant. In the equity market, the price pressure peaks at 2.45% on day 8 with a *t*-statistic of 2.17. In the government bond market, the price pressure reaches -33.2 basis points on day 11 with a t-statistic of -1.79.

3.3 Placebo Tests

To ensure that these price pressure patterns are not driven by recent returns in the equity and bond markets that drive the FyF recommendation in the first place, we perform a placebo test. We select placebo dates during a similar 31-month period exactly a decade earlier from July 2001 to January 2004. A sell equity event is identified as a day when the two-day cumulated return on equity is -2% or less and the government bond index return is 0.15% or more. A buy equity event is identified as a day when the two-day cumulated return on equity is 2% or more and the government bond index return is -0.15% or less. These return cutoff points are chosen to match the averages preceding the actual recommendation dates. We also eliminate days when the implied recommendation is already in place or when recommendations are separated by less than 5 business days. In other words, we try to pick dates that resemble the actual FyF recommendation dates in terms of prior market conditions. There are also 15 dates satisfying the selection criteria in our placebo sample period, exactly the same as in the actual sample period ten years later.

We then repeat the event studies in Table 4 using these placebo event dates. The results are reported in Table 5. We do not see any significant price pressure patterns in either the equity market or in the bond market, confirming that the price pressure associated with the actual FyF recommendations is not driven by random chance, nor some short-term autocorrelations in Chilean financial markets.

3.4 Robustness and Sub-Sample Analysis

As mentioned previously, FyF was particularly accurate in its first recommendation on July 27, 2011. The equity market index dropped by almost 7% during the subsequent week. To make sure that this one event is not driving our price pressure results, in Table 6, we repeat the regressions in Table 4 excluding sequentially the first four recommendation events. It is clear that the price pressure is not driven by the first event. After excluding the first FyF recommendation, we still observe a significant 1.55% cumulative price pressure in the equity market by day 8, and 0.25% cumulative price pressure in the government bond market by day 11. Excluding the second, third, and fourth events give similar results, although we lose statistical significance as we go from 15

observations to only 11 observations.

The placebo test confirms that our findings are not driven by a simple trading rule based on recent returns in the equity and bond markets. As an additional robustness check, we also directly control for past returns and other factors that may trigger FyF recommendations in calendar time regressions and show that they are not driving our results. The results are reported in Table 7. In these time-series regressions, we regress Chilean daily equity or bond index returns on event day indicator variables and additional control variables. The coefficients on each event day indicator variable thus isolate the magnitude of the price pressure on that day.

In panel (a) the dependent variable is the return of Santiago's stock exchange selective equity index (IPSA). In panel (b) the dependent variable 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 an email recommendation was sent. The indicator variables are adjusted to enable the comparison across the two recommendation types. Thus, the day 'indicator variables are positive when recommending to buy equity and negative when recommending to sell equity. We analyze three sets of control variables: The set I includes the weekly returns in each of the four previous weeks and the sums of the squared daily returns in the same weeks; the set II includes the PE ratio, the 2- and 10-yr government bond yields, and the lagged inflation; the setIII includes the contemporaneous daily return of the MSCI Latam Index. The PE ratio 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.

We find a consistent pattern across different regression specifications. For example, the regression in column (5) of Panel (a) includes all control variables (I, II, and III) that may affect the equity markets in Chile. We first notice the significantly positive returns during each of the two days prior to the FyF recommendation, this is consistent with our earlier findings in Table 3 that suggest a trend-chasing type of strategy used by FyF: they are more likely to recommend buying (selling) fund A after observing positive (negative) returns in the equity market. Note that the FyF recommendations are issued after the market close on event day 0 after FyF observes the return on that day.

We observe a large and significant price pressure on day 1 of 67 basis points. This positive

return is unlikely to be completely driven by the positive autocorrelation in the Chilean equity index for two reasons. First, we explicitly control for past returns up to day 0 in the regression. Second, the magnitude of the return on day 1 is even higher than that on day 0 (67 basis points vs. 66 basis points) while the daily autocorrelation coefficient in the Chilean equity index is only 0.16.

An interesting pattern we observe regarding the price pressure is that it is not evenly distributed across event days. There is a large and significant price pressure on day 1 (67 basis points), significant but smaller price pressure on days 3 and 6 (36 basis points and 42 basis points), and another large and significant price pressure on day 8 (56 basis points), followed by significant reversals on days 9 and 10.

There are several reasons why the largest price pressure takes place on day 1. As the FyF recommendations trigger more and more fund switches over time, pensions funds no doubt become aware of them. Anticipating large fund switches in the near future upon a new recommendation, pension funds may choose to start trading on day 1 already rather than waiting until day 4 when these switches have to be implemented. In addition, smart investors, anticipating pension funds' trading in the near future and the resulting price pressure, may choose to "front-run" pension funds' trades. Since FyF recommendations are sent out after the market closes on day 0, the earliest possible time they could trade is on day 1. These front-running trades effectively shift the cumulative price pressure to earlier days. In the next few days, as these smart investors turn around and liquidate their positions by trading with pension funds in a more orderly fashion without causing too much net order imbalance, we do not necessarily observe significant price pressure on every single day.

The fact that significant price pressure can be found as late as days 6 and 8 can be explained by the 5% rule. As seen from Figure 2, dollar flows resulted 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, it may force the pension funds to extend their trades by another 4 or 5 days after day 4. Since both pension funds and smart investors are likely to underestimate these largest fund switches, these residual trades that are forced beyond day 6 are less likely to be met by ready counterparties taking the other side of the trade, and therefore more likely to cause price pressure, followed by immediate price reversals. Additional sample period cuts in Table 8 provide supporting evidence for our explanation. Panel (a) cuts our sample into the first half (the first 8 recommendations) and the second half (the last 7 recommendations). It is evident that price pressure tends to be much stronger in the second half, consistent with Figure 1 where larger fund switches occur during the last 7 recommendations. In addition, we observe large and significant price pressure on the first day only in the second half, consistent with the notion that some smart investors become aware of the FyF-triggered fund switches over time and start to front-run pension funds' trades immediately after the recommendation.

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 groups based on the percentage fund flow to fund E during the recommendation month. The high-flow sample consists of recommendations during months when fund E flow exceeds 5% (in absolute term). These months include August 2011 (A to E), April 2012 (A to E), September 2012 (A to E), January 2013 (E to A), April 2013 (A to E), July 2013 (E to A), August 2013 (A to E), September 2013 (E to A), and January 2014 (A to E). The average absolute fund E flow across these high-flow months is 18.7%, which requires on average 4 days after day 4 to switch. Indeed, Panel (b) of Table 8 documents significant price pressure on day 6 and 8 among these high-flow months. In sharp contrast, there is no significant price pressure beyond day 1 during the remaining low-flow months.

Panel (c) splits our sample based on the direction of switches. Recall 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 E, then stocks have to be sold almost immediately in order to raise cash to transfer to fund E. On the other direction, when the recommendation is to switch from fund E to 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.

3.5 Price Pressure and Abnormal Trading in the Cross Section

In this section we investigate whether the price pressure is more pronounced for securities that are disproportionately held by Chilean pension funds.

Similar to Figure 3, Figure 4 contains the same cumulative average return plots in both the

equity and the bond markets, except that we separate large stocks from small stocks, and long-term bonds from short-term bonds. Large stocks correspond to the ten largest stocks in Santiago's stock exchange and small stocks are the the bottom ten stocks among the 50 largest stocks. Long term bonds correspond to government bonds with maturities of ten years or longer and short term bonds are the remaining government bonds.

The left panel shows that while both types of stocks experience price pressure that are reversed eventually, the pattern is more prominent for larger stocks. The cumulative average return peaks at 2.5% for large stocks and only 1.6% for small stocks. Similarly the right panel shows that long-term bonds experience stronger price pressure than the 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.

Our coordinated noise trading hypothesis suggests that the stronger price pressure on large stocks and long-term bonds has to come from the fact that they are traded more as the pension fund managers are implementing the switches between funds A and E. Figure 5 confirms this fact. It plots the cumulative daily abnormal turnover in the equity and bond markets during the same event window. Daily abnormal turnover is defined as the turnover on that day divided by a measure of the normal daily turnover minus 1. For stocks, the normal daily turnover is the average daily turnover in the previous year. We use the average over a year to define normal turnover since some stocks, especially small stocks, are traded sparsely and in a lumpy way. For bonds, it is defined as the average daily turnover in the 5 trading days prior to the event as government bonds are heavily traded. These daily abnormal turnovers are then cumulated from event day 1.

The left panel shows that large stocks experience heavier than usual trading for at least 11 days after the recommendation. The right panel shows abnormal trading on both long-term and short-term bonds, but more so for long-term bonds. These turnover patterns are consistent with their price pressures.

Tables 9 to 13 confirm the findings in Figures 4 and 5 with panel regressions. Table 9 examines the post-event stock returns in the cross section. Columns 1-3 report the results from Fama-MacBeth cross-sectional regressions. Separately for each event day, we regress the cumulative stock returns (for the next 5, 8, and 10 trading days) on stock characteristics:

$$CAR_i = \beta Z_i + \varepsilon_i,\tag{1}$$

where *i* is stock *i* and Z_i is a set of stock characteristics. The regression coefficients β are then averaged across events and reported. Column 2 reports a positive and significant coefficient of 0.006 on the market cap variable, suggesting that larger stocks indeed experience significantly higher cumulative returns after eight trading days than smaller stocks.

In columns 4-5, we run panel regressions pooling all stocks of a given characteristic (e.g., large stocks in column 4 and small stocks in column 5) and event days t + j, with j = 1, ..., 15.

$$CAR_{i,t+j} = \sum_{j=1}^{15} \beta_j Event Day_j + \varepsilon_{i,t+j}.$$
(2)

Consistent with Figure 4, column 4 shows that large stocks experience positive and significant price pressure from t + 1 up to t + 9. The cumulative average returns peak at 2.5% on day t + 8 and then reverse afterwards. By day t + 15, the price pressure is almost completely reversed. The pattern for small stocks, as shown in column 5, is similar but less pronounced. Finally, column 6 reports the differences between coefficients in columns 4 and 5. It again confirms that larger stocks experience significantly higher price pressure than smaller stocks.

Table 10 repeats the analysis in Table 9 for the cross-section of government bonds. The crosssection consists of primarily ten bonds: nominal bonds with maturities of 2, 5, 7, and 10 years and inflation-indexed bonds with maturities of 2, 5, 6, 10, 20, and 30 years. Columns 1 to 3 confirm that long-term bonds (with higher durations) experienced more negative cumulative post-event returns (consistent with Figure 4). Pooled panel regressions in columns 4 to 6 suggest that (1) long-term bonds experienced significant cumulative average returns 10 trading days after the event; and (2) the price pressure on long-term bonds are significantly stronger than that on the short-term bonds.

The regressions in Table 11 are very similar to those in Table 9 except that the independent variables are cumulative abnormal turnovers (CATs) on stocks rather than their cumulative average returns (CARs). Abnormal Turnover (AT) is defined as the ration between turnover and normal turnover minus one, where normal turnover is the average turnover in the year before each event. We use the average in one year to define normal turnover since some stocks, especially the small stocks, are traded sparsely and in a lumpy way. These abnormal turnovers are then cumulated from event day 1 to get cumulative abnormal turnovers (CATs).

Consistent with the return results in Table 9, columns 1 to 3 show the CATs to be positively

related to the size of the stocks: the FyF recommendations lead to greater abnormal trading in larger stocks. In fact, columns 4 to 6 suggest that the abnormal trading concentrated among large stocks post events, consistent with the notion that pension fund managers, in order to satisfy the switches to and from their equity portfolios, trade mostly large stocks. This is not surprising as large stocks dominate the portfolio holdings and are usually more liquid. Column 4 also shows that CAT among large stocks keeps on increasing before leveling off on t + 12. The lack of reversal suggests that the abnormal trading reflects excessive noise trading rather than an effort by portfolio managers to optimally time their trades.

The same analysis in Table 10 is extended to the government bond market in Table 12. Here, the abnormal cumulative turnovers are defined similarly except that normal turnover is the average turnover in the prior week rather than in the prior year as in the case of stocks. This is because government bonds are heavily traded. Columns 1 to 3 confirm that long-term bonds (with higher durations) experience more abnormal trading post-event (consistent with Figure 5). Pooled panel regressions in columns 4 to 6 suggest that government bonds experience significant abnormal trading after the event and that the abnormal trading is heavier on long-term bonds than on the short-term bonds. Table 13 repeats the analysis in Table 12 except that abnormal trading is measured with the number of trades in bonds rather than the dollar volume. The results are very similar.

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 coincide 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 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.

4 Additional Results

4.1 Return to Noise Trading

from FyF? To investigate whether investors actually make money from following the FyF recommendations, we 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 email (FyF). With strategy (3), we assume that the recommendation is sent out on day t, the switches will be made at the market price at day t + 2. Since the recommendation is sent out after market close during day t, most investors will be requesting switches after day t (see Figure 1) and the switches will be made with prices after t+2, likely worse due to the price pressure we document. As such, the return to strategy (3) likely serves as an upper bound on 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 its funds A to E. As such, we will 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 types across different AFPs are very similar, primarily due to the minimum yield rule imposed by the regulator and the resulting herding investment behavior. These average cumulative returns are plotted in Figure 6.

The top panel shows the cumulative returns of an investment of \$1 on each strategy, starting from the first FyF recommendation date (July 27, 2011). This is the performance graph that is prominently displayed in FyF's marketing material. Indeed, it shows that the FyF "market timing" strategy outperforms both funds A and E by March 2014. The cumulative return is 15.8% on fund A and 21.0% on fund E. The FyF strategy, however, generates a cumulative return of 26.5%. In addition, the FyF strategy almost always outperforms the other two passive strategies.

A closer look at the investment strategy suggests that the superior performance of FyF's recommendations mostly comes from its first recommendation (a switch from fund A to E on July 27, 2011). This switch successfully avoids the 7% drop in the stock market in the subsequent month (as evidenced in the dip on fund A return). This turns out to be just beginner's luck. If the first FyF recommendation is skipped by starting the \$1 investments in the three strategies from its second recommendation date (October 12, 2011), the magic of FyF is gone as shown in the middle panel. Now the cumulative return of the FyF strategy is only 22.4% by March 2014, which is lower than that on fund A (26.5%).

Finally, if one starts the \$1 investments from the fifth recommendation date (March 29, 2012) as many investors do (see Figure 1), 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 they trigger are likely to reflect noise trading.

4.2 Investor Demographics and Noise Trading

We conjecture that younger investors are more likely to be attracted by FyF given FyF's marketing strategy based on the internet and social media. One pension company (AFP), called Modelo, has an investor base that is heavily tilted towards younger investors (see Table 14 Panel A) since it just started in 2010. Most of Modelo's investors are young because, by offering a fee that was significantly lower than the industry average, Modelo won the first auction organized by the government to allocate entrants to the labor force. Given our conjecture we expect the flows to Modelo to be more sensitive to FyF's emails. In Table 14 Panel B we regress the monthly flows to pension funds on indicator 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 funds A, while the flow to Modelo's fund A is 7.8% higher (coefficient on the interaction). 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 the largest outflows (7.19% higher) when FyF recommends switching towards fund A. FyF recommendations to switch to fund E are associated with an average outflow from funds 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 emails as one would expect from a fund with a younger investor base.

4.3 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 cross-sectional variation in the stock market to study the impact of noise trading triggered by FyF recommendations on stock return volatility. The intuition is as follows: as the 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 and greater volatility.

We follow the framework of Greenwood and Thesmar (2011). We measure the noise-tradinginduced price pressure from fund A 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 cap of stock i. Panel A of Table 15 first confirms the earlier results that stocks with higher noise-tradinginduced price pressure indeed suffer from larger price impact (in absolute terms) following the FyF recommendations. These correlations are highly significant especially on the first day and by day 8. Momentum is the cumulated return between months t - 12 and t - 2. Market cap is the logarithm 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. All regressions include stock fixed effects and month fixed effects.

We then regress monthly return volatility on the price pressure measure. Panel B in Table 15 shows a strong link between predicted price pressure and return volatility. A 1% increase in the price pressure leads to a 0.75% increase in stock monthly volatility, even after controlling for other stock characteristics and past volatility.

4.4 Response from Pension Funds

Given our findings so far that fund switches can generate large price pressure and result in excessive volatility, it is natural to analyze 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 email and ends in December 2013.

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

5 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 the 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 risk-free government bonds), or vice versa, in an attempt to "time the market." An investment advisory firm called "Felices y Forrados" (FyF) gained tremendous popularity in 2011 by providing fund switching signals. These signals serve 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.

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Number of voluntary daily fund switches since January 2011



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 an email with a switch recommendation. Source: provided by the Superintendencia de Pensiones using administrative records; vertical lines with dates were added by the authors.



Figure 2: 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.



Figure 3: Cumulative average returns for the 15 email 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 email recommendation is sent, which occurs after the market has closed. The line shows the simple average of the cumulative index returns for the 15 events on the corresponding event date.



Figure 4: Cumulative average returns for the 15 email recommendations. The top figure shows the results for Santiago's 50 largest stocks by market value. The bottom figure corresponds to the most representative government bonds traded in Chile's financial market. Day 0 is defined as the day when the email recommendation is sent, which occurs after the market has closed. The line shows the simple average of the cumulative index returns for the 15 events on the corresponding event date. Large stocks correspond to the 10 largest stocks in Santiago's stock exchange, small stocks are the bottom 10 stocks among the 50 largest stocks. Long bonds correspond to bonds with maturities of 10 years or more, short bonds are the bonds with maturities shorter than 10 years.



Figure 5: Cumulative abnormal turnover for stocks and government bonds around the email recommendations. Abnormal turnover is accumulated starting on day 1 because it corresponds to the first trading day since the email recommendation is sent. Fund switches requested by investors are effective two business days after the initial filing. Large stocks correspond to the 10 largest stocks in Santiago's stock exchange, small stocks are the bottom 10 stocks among the 50 largest stocks. Long bonds correspond to bonds with maturities of 10 years or more, short bonds are the bonds with maturities shorter than 10 years.



Figure 6: 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) Buyand-hold fund E (Fund E); (3) Switching between fund A and E following FyF's recommendations immediately after receiving the email (FyF). We consider three cases: we invest a dollar in each strategy starting from (1) the first FyF email (Jul 27, 2011); (2) the second FyF email (Oct 12, 2011); the fifth email (Mar 29, 2012).



Figure 7: Portfolio holdings of fund A and E over time. We plot the portfolio weights of cash, ETF, 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 email 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. "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.

	Par	nel (a)						
Fund	А	В	С	D	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 (days)	3655	4006	3193

Table 2: List of portfolio recommendations sent by FyF to their clients. Email is sent to subscribers after market transactions have closed on the evening of the day in columna "Date sent". For the first 15 emails the recommendations considered only strategies between equity (fund A) and fixed income (fund E). Starting

	Email	Recommen	ded change	Buying pressure on
Number	Date sent	From fund	To fund	Dujing probaro on
1	July 27, 2011	А	Е	Bonds
2	October 12, 2011	${ m E}$	А	Equity
3	November 22, 2011	А	${ m E}$	Bonds
4	January 11, 2012	${ m E}$	А	Equity
5	March 29, 2012	А	${ m E}$	Bonds
6	June 19, 2012	${ m E}$	А	Equity
7	June 28, 2012	А	${ m E}$	Bonds
8	July 19, 2012	\mathbf{E}	А	Equity
9	August 29, 2012	А	\mathbf{E}	Bonds
10	January 2, 2013	\mathbf{E}	А	Equity
11	April 2, 2013	А	\mathbf{E}	Bonds
12	July 17, 2013	\mathbf{E}	А	Equity
13	August 16, 2013	А	\mathbf{E}	Bonds
14	September 6, 2013	\mathbf{E}	А	Equity
15	January 24, 2014	А	\mathbf{E}	Bonds
16	March 6, 2014	\mathbf{E}	0.5C + 0.5E	
17	August 5, 2014	0.5C + 0.5E	Ε	
18	August 19, 2014	Ε	0.5A + 0.5E	

Table 3: Determinants of the FyF recommendations. We estimate an ordered probit model where the dependent variable takes the value of one in days with an email recommending a switch towards fund A, zero in days without emails, and minus one in days with an email recommending a switch towards fund E. The explanatory variables in the ordered probit model are lagged returns and fundamentals such as the price-earnings ratio, bond yields, or inflation.

Variable	(1)	(2)	(3)	(4)
Chilean equity index return week -1	7.7645**			4.4454
	(3.142)			(5.060)
Chilean equity index return week -2	-3.8912			-1.6991
	(3.138)			(4.917)
Chilean equity index return week -3	3.7794			2.1759
	(4.292)			(4.120)
Chilean gov index return week -1	-10.9279			-9.5914
	(15.831)			(13.884)
Chilean gov index return week -2	-12.9587			-13.7561
	(15.881)			(17.323)
Chilean gov index return week -3	30.8428			24.4325
	(23.169)			(23.160)
Exchange rate change week -1		-14.5103^{***}		-9.2115*
		(5.069)		(5.366)
Exchange rate change week -2		-0.0634		-2.3533
		(4.515)		(5.182)
Exchange rate change week -3		7.5705		11.4807*
		(7.511)		(6.352)
Price-earnings ratio		0.0042		0.0211
		(0.045)		(0.055)
Yield 2yr bond		-17.0422		-12.7478
		(19.552)		(19.814)
Yield 10 yr bond		-30.8488		-39.7774
		(40.594)		(47.751)
Inflation		-51.9355		-55.4331
		(35.259)	6 2222**	(34.608)
MSCI Latam index return week -1			6.2323**	1.7423
			(2.679)	(3.486)
MSCI Latam index return week -2			-1.7713	-1.7838
			(2.473)	(3.963)
MSCI Latam index return week -3			4.8693	(4.120)
			(3.415)	(4.136)
Pseudo R2	0.0409	0.0456	0.0363	0.0917
Observations	1,090	997	$1,\!110$	997

Table 4: Event study calculation of cumulated raw returns in the Chilean financial market around the dates when email recommendations were sent. "Day" column indicates the event time taking as day 0 the day when recommendation email was sent, and this is done *after* the market has closed. Equity index corresponds to the results using Santiago's stock exchange selective equity index (IPSA). Government bond index are the results using the "Dow Jones LATixx Chile Government Bond Index" produced by LVA Indices. CAR are the average cumulated raw returns starting day 1, and the average was calculated using the 15 events. t-stat are the cross section t-tests. Note: *** p < 1%, ** p < 5%, * p < 10%.

Dav	Equity]	Index	Governmen	nt Bond Index	Ν
Day	CAR	t-stat	CAR	t-stat	11
1	0.0063^{*}	(2.12)	0.0000	(0.08)	15
2	0.0052	(1.33)	-0.0001	(-0.15)	15
3	0.0090	(1.59)	-0.0008	(-0.89)	15
4	0.0074	(1.45)	-0.0009	(-1.04)	15
5	0.0068	(1.37)	-0.0009	(-1.01)	15
6	0.0114^{*}	(1.79)	-0.0007	(-0.70)	15
7	0.0142^{*}	(1.88)	-0.0007	(-0.53)	15
8	0.0245^{**}	(2.17)	-0.0014	(-0.99)	15
9	0.0164^{*}	(1.89)	-0.0018	(-1.38)	15
10	0.0123	(1.50)	-0.0023	(-1.45)	15
11	0.0138^{*}	(1.88)	-0.0033*	(-1.79)	15
12	0.0111	(1.44)	-0.0029	(-1.38)	15
13	0.0077	(1.00)	-0.0028	(-1.48)	15
14	0.0051	(0.65)	-0.0030	(-1.42)	15
15	0.0036	(0.41)	-0.0036	(-1.65)	15

Table 5: Event study calculation of cumulated average returns in the Chilean financial market around the placebo dates selected between July 2001 and January 2004, this is exactly one decade before FyF started sending email recommendations. A sell equity event was identified as a day when the two-day cumulated return on equity was -2% or less and the government bond index return was 0.15% or more. A buy equity event was identified as a day when the two-day cumulated return on equity was 2% or more and the government bond index return was -0.15% or less. Consecutive days with the same recommendations were eliminated. We also eliminated days when the implied recommendation was already in place or when recommendations were separated by less than 5 business days. "Day" column indicates the event time taking as day 0 the day when recommendation email was sent, and this is done after the market has closed. Equity index corresponds to the results using the "Dow Jones LATixx Chile Government Bond Index" produced by LVA Indices. CAR are the average cumulated raw returns starting day 1, and the average was calculated using all 15 placebo events found in the pre-FyF sample. t-stat are the cross section t-tests. Note: *** p<1%, ** p < 5%, * p < 10%.

Dav	Equity 1	Index	Government	Bond Index	Ν
Day	CAR	t-stat	CAR	t-stat	1,
1	0.000466	(0.14)	0.000344	(1.21)	15
2	-0.00187	(-0.32)	-0.0000212	(-0.03)	15
3	-0.00157	(-0.21)	0.0000780	(0.09)	15
4	-0.00368	(-0.55)	-0.000195	(-0.19)	15
5	-0.00147	(-0.22)	-0.0000534	(-0.04)	15
6	-0.00100	(-0.12)	-0.000885	(-0.71)	15
7	-0.00158	(-0.16)	-0.000694	(-0.49)	15
8	0.00463	(0.42)	-0.000386	(-0.24)	15
9	0.00597	(0.51)	-0.000830	(-0.47)	15
10	0.00751	(0.63)	-0.000968	(-0.51)	15
11	0.00569	(0.46)	-0.00118	(-0.62)	15
12	0.00545	(0.44)	-0.00125	(-0.64)	15
13	0.00379	(0.31)	-0.000516	(-0.27)	15
14	-0.000112	(-0.01)	-0.000679	(-0.34)	15
15	-0.00147	(-0.11)	-0.000955	(-0.42)	15

(t-test critical value=2.13), $*p < 10\%$.
each test is shown at the bottom of the table. t-stat are the cross section t-tests for the AR and CAR. Note: $***p < 1\%$, $**p < 5\%$
CAR are the cumulated average returns starting day 1 for the events indicated on the table header, the number of events included in
(IPSA). Government bond index are the results using the "Dow Jones LATixx Chile Government Bond Index" produced by LVA Indices.
his is done after the market has closed. Equity index corresponds to the results using Santiago's stock exchange selective equity index
rom the estimation samples."Day" column indicates the event time taking as day 0 the day when recommendation email was sent, and
Table 6: Event study calculation of cumulated average returns in the Chilean financial market removing the initial email recommendations

			Pa	nel (a): Ec	quity return	Ţ					Panel (ł): Govt b	ond index	return		
\mathbf{Day}	From 2nd	d event	From $3r$	d event	From 4t.	h event	From 5t]	h event	From 2n	id event	From 3r	d event	From 4t]	h event	From 5tl	ı event
	\mathbf{CAR}	t-stat	CAR	t-stat	\mathbf{CAR}	t-stat	\mathbf{CAR}	t-stat	\mathbf{CAR}	t-stat	\mathbf{CAR}	t-stat	\mathbf{CAR}	t-stat	\mathbf{CAR}	t-stat
1	0.0071^{**}	(2.30)	0.0074^{**}	(2.25)	0.0058^{*}	(1.86)	0.0061^{*}	(1.80)	0.0000	(0.08)	-0.0002	(-0.33)	0.0000	(-0.02)	-0.0001	(-0.25)
7	0.0057	(1.39)	0.0062	(1.41)	0.0044	(1.01)	0.0048	(1.01)	0.0000	(0.00)	-0.0003	(-0.42)	-0.0001	(-0.18)	-0.0004	(-0.56)
°,	0.0108^{*}	(1.88)	0.0116^{*}	(1.89)	0.0091	(1.49)	0.0096	(1.43)	-0.0008	(-0.79)	-0.0011	(-1.10)	-0.0006	(-0.63)	-0.0011	(-1.24)
4	0.0076	(1.39)	0.0072	(1.23)	0.0064	(1.02)	0.0065	(0.94)	-0.0007	(-0.80)	-0.0010	(-1.05)	-0.0008	(-0.75)	-0.0013	(-1.32)
Ŋ	0.0056	(1.09)	0.0045	(0.82)	0.0035	(0.60)	0.0029	(0.45)	-0.0007	(-0.71)	-0.0008	(-0.76)	-0.0004	(-0.39)	-0.0010	(-1.05)
9	0.0078	(1.38)	0.0070	(1.17)	0.0084	(1.32)	0.0078	(1.12)	-0.0002	(-0.21)	-0.0002	(-0.20)	0.0000	(-0.01)	-0.0006	(-0.54)
4	0.0094	(1.49)	0.0078	(1.19)	0.0088	(1.25)	0.0081	(1.05)	0.0000	(-0.01)	0.0001	(0.08)	0.0002	(0.12)	-0.0004	(-0.33)
œ	0.0155^{*}	(2.11)	0.0131	(1.75)	0.0145^{*}	(1.82)	0.0149	(1.70)	-0.0005	(-0.41)	-0.0003	(-0.25)	-0.0002	(-0.17)	-0.0008	(-0.59)
6	0.0110	(1.50)	0.0093	(1.21)	0.0096	(1.15)	0.0097	(1.05)	-0.0010	(-0.91)	-0.0007	(-0.61)	-0.0005	(-0.38)	-0.0011	(-1.03)
10	0.0085	(1.09)	0.0060	(0.76)	0.0059	(0.68)	0.0061	(0.65)	-0.0014	(-0.98)	-0.0008	(-0.58)	-0.0004	(-0.28)	-0.0011	(27.0-)
11	0.0119	(1.56)	0.0070	(1.11)	0.0083	(1.23)	0.0087	(1.18)	-0.0025	(-1.39)	-0.0012	(-0.89)	-0.0009	(-0.64)	-0.0016	(-1.18)
12	0.0097	(1.18)	0.0044	(0.65)	0.0060	(0.85)	0.0061	(0.78)	-0.0020	(-0.98)	-0.0004	(-0.30)	0.0000	(0.00)	-0.0007	(-0.49)
13	0.0054	(0.69)	0.0008	(0.12)	0.0017	(0.22)	0.0014	(0.18)	-0.0019	(-1.06)	-0.0006	(-0.44)	-0.0002	(-0.17)	-0.0010	(-0.81)
14	0.0029	(0.36)	-0.0020	(-0.29)	-0.0013	(-0.17)	-0.0026	(-0.33)	-0.0021	(-1.02)	-0.0004	(-0.33)	-0.0001	(-0.05)	-0.0008	(-0.68)
15	-0.0001	(-0.01)	-0.0051	(69.0-)	-0.0056	(-0.70)	-0.0085	(-1.04)	-0.0025	(-1.23)	-0.0008	(-0.67)	-0.0003	(-0.25)	-0.0011	(-1.12)
Z	14		13		12		11		14		13		12		11	

		Panel	(a): Equity re	eturn			Panel (b): G	ovt bond inc	dex return	
Variables	(1)	(2)	(3)	(4)	(2)	(9)	(2)	(8)	(6)	(10)
Day -3	0.0049^{*}	0.0049^{*}	0.0051^{*}	0.0041^{*}	0.0044^{**}	-0.0005	-0.0005	-0.0005	-0.0004	-0.0005
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day -2	0.0015	0.0014	0.0018	0.0008	0.0011	0.0003	0.0002	0.0003	0.0003	0.0003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day -1	0.0095^{***}	0.0092^{***}	0.0097^{***}	0.0059^{***}	0.0060^{***}	+2000.0-	-0.0008*	-0.0007*	-0.0005	-0.0005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day 0	0.0106^{***}	0.0104^{***}	0.0108^{***}	0.0066^{***}	0.0066^{***}	-0.0008*	-0.0008*	-0.0008*	-0.0005	-0.0005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(000.0)	(0.000)	(0.000)
лау 1	(0 003)	(0 003)	(0 003)	(2000)	(0 003)	-0.000 D)	(0000)	-0.000 D)	(0000)	(0000)
Day 2	-00009	-0.003	-0.007	0.0007	0.0011	-0.0003	-0.003	-0.0003	-0.0004	-0.0004
•	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.00)	(0.00)	(0.00)	(0.000)	(0.000)
Day 3	0.0041^{*}	0.0049^{**}	0.0043^{*}	0.0032	0.0036^{*}	-0.0008**	+2000.0-	-0.0008**	-0.0008*	-0.0007*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.00)	(0.00)	(0.000)	(0.000)
Day 4	-0.0016	-0.0006	-0.0016	-0.0015	-0.0011	-0.0001	-0.0000	-0.0001	-0.0001	-0.0001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.00)	(000.0)	(0.000)	(0.000)
Day 5	-0.0006	0.0001	-0.0005	-0.0022	-0.0021	-0.0000	-0.0000	-0.0001	0.0001	0.0001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day 6	0.0046^{*}	0.0049^{**}	0.0047^{*}	0.0044^{**}	0.0042^{**}	0.0002	0.0002	0.0002	0.0003	0.0002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day 7	0.0028	0.0030	0.0029	0.0011	0.0009	0.0000	0.0000	0.0000	0.0002	0.0001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day 8	0.0103^{***}	0.0104^{***}	0.0104^{***}	0.0059^{***}	0.0056^{***}	-0.0008*	-0.0008**	-0.0008*	-0.0004	-0.0004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day 9	-0.0081^{***}	-0.0081^{***}	-0.0080***	-0.0043^{**}	-0.0046^{**}	-0.0003	-0.0003	-0.0003	-0.0006	-0.0006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(000.0)	(0.000)	(0.000)
Day 10	-0.0040^{*}	-0.0043^{*}	-0.0040*	-0.0042^{**}	-0.0046^{**}	-0.0006	-0.0006	-0.0006	-0.0006	-0.0005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.00)	(0.000)	(0.000)
Controls?	None	Ι	II	III	I, II, III	None	I	Π	III	I, II, III
Z	1,125	1,105	266	1,125	297	1,104	1,084	266	1,104	266
R^{2}	0.076	0.093	0.089	0.344	0.371	0.018	0.033	0.023	0.070	0.101

Table 8: C the return ((b) separate separates at day corresp absolute val include the gov bond yi the value re Standard er	'alendar tim of Santiago's se the email coording to t onds to the onds to the une (Day du ue (Day du cumulative elds, lagged ported 30 tr rors reporte	the regression s stock excl s into those the direction i - th day mmies are returns in e inflation, a: ading days d in parentl	as of daily 1 nange select $\frac{1}{2}$ that gener after an er positive wh each of the each of the ond the cont earlier. La hesis. *** p	returns for ive equity rated high ommended mail recom four previc emporaneo gged inflati < 0.01, **	Chilean equivalent constraints of the constraint of the constrain	inity, from J A). In pane by and 9 to ay i'' varial was sent. S uny equity i uny equity i und the sum rrn of the N p < 0.1.	anuary 201 (a) we est 15) and lo les corresp iell and bu und negativ is of the sq fSCI Latan nflation ra	0 to June simate the w monthly ond to dum y recomme e when rec uared retur uared retur te of the m	2014. The effect for fin effect for fin flows (emai nmy variable indations arr onthe sa is taken fr onth corres	dependent st 8 and tl ils 2, 3, 4, ss that take e restricted to sell equ ume weeks, om Bloomb oonding to	variable in ne last 7 en and 6 to 8) the value to have th ity). Conti PE ratio, 2 erg and co 30 trading	all panels is nails. Panel . Panel (c) of one if the e impact in ol variables P- and 10-yr responds to days earlier.
	Fan First 8	iel (a): Early emails	vs Kecent em Lact 7	alie		l (b): By size	of flows indu	lced flow	Salling	c): By type o	It recommend Burging	ation
			TASU	ellialis	118111	MOII	FOW	MOIT	Biiiiac	equity	Duying	
Day -3	0.0109^{***}	0.0111^{***}	-0.0003	-0.0012	-0.0015	-0.0011	0.0191^{***}	0.0184^{***}	0.0018	0.0018	0.0085**	0.0082^{***}
Dav -2	(0.004) 0.0014	(0.003) 0.0004	(0.003) 0.0016	(0.003) 0.0016	(0.003) 0.0007	(0.003) 0.0007	(0.004) 0.0028	(0.004) 0.0026	(0.003) 0.0015	(0.003) 0.0005	(0.004) 0.0014	(0.003) 0.0011
د ا	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Day -1	0.0104*** (0.003)	0.0061^{**}	0.0086^{***}	0.0059^{**}	0.0096*** (0.003)	0.0068^{***}	0.0094** (0.004)	0.0055	0.0088**	0.0054* (0.003)	0.0102*** (0.003)	0.0071** (0.003)
Day 0	0.0084^{**}	0.0056^{*}	0.0129^{***}	0.0080***	0.0133^{***}	(conco) 0.0077***	0.0059	0.0049	0.0120^{***}	0.0078^{***}	$(0.003^{***}$	0.0059**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Day 1	0.0042 (0.003)	0.0048 (0.003)	0.0113^{***} (0.003)	0.0088^{***}	0.0078^{***}	0.0059^{**}	0.0077^{**}	0.0078^{**}	0.0086^{**}	0.0056^{*}	0.0069^{**}	0.0075^{***} (0.003)
Day 2	-0.0038	-0.0005	0.0021	0.0027	0.0013	0.0019	-0.0048	-0.0013	0.0027	0.0039	-0.0044	-0.0022
Dot: 9	(0.003)	(0.003)	(0.003) 0.0060**	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003) 0.0005	(0.003)
o ybu	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Day 4	-0.003	-0.0003	-0.0032	-0.0023	0.004	-0.0006	-0.0047	-0.0024	-0.0005	-0.0001	-0.0029	-0.0019
Day 5	(0.003)	(0.003) -0.0023	(0.003) -0.0037	(0.003) -0.0023	(0.003) -0.0012	(0.003) -0.0004	(0.003)	(0.003)-0.0044	(0.003) -0.0006	-0.0009 -0.0009	(0.003) -0.0005	(0.003) - 0.0031
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lay u	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	0.003) (0.003)	(0.003)	(0.003)	0.003) (0.003)	(0.003)
Day 7	0.0062^{*}	0.0040	-0.0010	-0.0025	0.0022	0.003	0.0038	0.0018	0.0063^{*}	0.0029	-0.0012	-0.0015
Dav 8	(0.003) 0.0115^{***}	(0.003) 0.0051^{*}	(0.0090^{***})	(0.003)	(0.003) 0.0152^{***}	(0.003) 0.0106^{***}	(0.004)	(0.003) -0.0015	(0.003) 0.0125^{***}	(0.003) 0.0075^{***}	(0.0079^{**})	(0.0037 0.0037
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Day 9	-0.0088***	-0.0055** (0.003)	-0.0072**	-0.0037	-0.0121*** (0.003)	-0.0068**	-0.0020	-0.0017	-0.0090*** (0.003)	-0.0045	-0.0070**	-0.0052* (0.003)
Day 10	-0.0044	-0.0034	-0.0036	-0.0054^{*}	-0.0050*	-0.0067**	-0.0026	-0.0014	-0.0054^{*}	-0.0061^{**}	-0.0024	-0.0028
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Controls?	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
\mathbb{N}^2	1,027 0.052	892 0.363	1,021 0.055	887 0.318	1,049 0.083	917 0.367	999 0.038	$862 \\ 0.325$	1,028 0.058	893 0.359	1,020 0.041	$884 \\ 0.314$

Table 9: Regressions of cumulative return for equity around email recommendations, each email recommendation is an event. Columns labeled "Cross section" corresponds to a regression where the dependent variable is the cumulative return of the 50 largest stocks in the Santiago stock market in the event dates marked on the column head. 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. Return volatility is the standard deviation of the returns. Columns labeled "Sorted by size" correspond to pooled regressions of the cumulative returns of Large and Small stocks for all event dates and events on event time dummies, where "Day t" is a dummy for the days that correspond to event time t for any of the events. Large stocks are the 10 largest stocks in Santiago's stock market, small stocks are the bottom 10 stocks among the 50 largest stocks. The last column is a pooled regression of the cumulative abnormal returns of large and small stocks, as previously defined, on a full set of event time dummies and the interaction between the event time dummies and a dummy for large stocks, we report the coefficients for these interactions. Note: Standard errors: robust in columns 1-3, clustered by event day in each event in columns 4-6. *** p < 0.01, ** p < 0.05, * p < 0.1.

Variables	(Cross section	on	Sort	ted by size	_ Large - Small
	Day 5	Day 8	Day 10	Large	Small	
ln Mkt cap	0.001	0.006**	0.002			
	(0.002)	(0.003)	(0.002)			
B/M	0.001	0.002	0.001			
	(0.002)	(0.003)	(0.003)			
MOM	0.002	0.010	0.005			
	(0.007)	(0.011)	(0.009)			
Ret Vol	-0.034	-0.046	-0.014			
_	(0.054)	(0.105)	(0.076)			
Day 1				0.006**	0.003*	0.003
				(0.003)	(0.002)	(0.002)
Day 2				0.005	0.005**	0.000
D				(0.004)	(0.002)	(0.004)
Day 3				0.010^{*}	0.005*	0.005
D ((0.005)	(0.003)	(0.005)
Day 4				0.008*	0.004	0.004
				(0.004)	(0.003)	(0.004)
Day 5				0.007^{*}	0.005	0.003
				(0.004)	(0.004)	(0.004)
Day 6				0.012^{++}	(0.008)	(0.005)
Derr 7				(0.000)	(0.005)	(0.004)
Day 7				(0.010^{-1})	(0.009)	(0.007)
Derr 9				(0.007)	(0.000)	(0.004)
Day 8				(0.025^{+1})	(0.010°)	(0.009)
Day 0				0.016**	0.009)	(0.003)
Day 9				(0.010)	(0.013)	(0.001)
Day 10				0.011	0.012	0.000)
Day 10				(0.008)	(0.012)	(0.007)
Day 11				0.013*	0.014**	-0.002
Dug 11				(0.007)	(0.006)	(0.006)
Day 12				0.010	0.014**	-0.004
2007 12				(0.007)	(0.007)	(0.006)
Dav 13				0.007	0.011	-0.004
				(0.008)	(0.007)	(0.007)
Day 14				0.005	0.010	-0.005
U				(0.008)	(0.007)	(0.007)
Day 15				0.003	0.010	-0.006
U				(0.009)	(0.007)	(0.008)
Fixed effects?	no	no	no	no	no	ves
Ν	664	662	660	a 2,250	2,162	4,412
R^2	0.003	0.011	0.001^{-4}	0.074	0.053	0.013

Table 10: Regressions of cumulative return government bonds around email recommendations, each email recommendation is an event. Columns labeled "Cross section" corresponds to a regression where the dependent variable is the cumulative return of the most representative Chilean government bonds in the event dates marked on the column head. Duration corresponds to the duration of each type of bond in the corresponding date. Nominal dummy takes a value of 1 for peso denominated bonds and 0 for (lagged) inflation indexed ones. Ln Amount Outstanding is the log of the outstanding value of all bonds of each type. Columns labeled "Sorted by maturity" correspond to pooled regressions of the cumulative returns of Long and Short bonds for all event dates and events on event time dummies, where "Day t" is a dummy for the days that correspond to event time t for any of the events. 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 last column is a pooled regression of the cumulative returns of all bonds on a full set of event time dummies and the interaction between the event time dummies and a dummy for long bonds, we report the coefficients for these interactions. Note: Standard errors: robust in columns 1-3, clustered by event day in each event in columns 4-6. *** p < 0.01, ** p < 0.05, * p < 0.1.

Variables	(Cross section	on	Sorted	by maturity	Long - Short
	Day 5	Day 8	Day 10	Long	Short	
Duration	-0.023*	-0.020	-0.042**			
	(0.013)	(0.019)	(0.021)			
Nominal dummy	-0.000	0.001	0.002			
	(0.001)	(0.002)	(0.002)			
Ln Amount	0.001	0.003	0.004^{*}			
Outstanding	(0.001)	(0.002)	(0.002)			
Day 1				0.000	-0.000	0.000
				(0.001)	(0.000)	(0.000)
Day 2				-0.000	-0.000	0.000
				(0.001)	(0.000)	(0.001)
Day 3				-0.001	-0.001	-0.001
				(0.002)	(0.001)	(0.001)
Day 4				-0.002	-0.000	-0.001
-				(0.002)	(0.001)	(0.001)
Day 5				-0.002	-0.001	-0.002*
				(0.002)	(0.001)	(0.001)
Day 6				-0.002	-0.001	-0.001
				(0.002)	(0.001)	(0.001)
Day 7				-0.002	-0.001	-0.001
				(0.002)	(0.001)	(0.001)
Day 8				-0.003	-0.001	-0.002
				(0.003)	(0.001)	(0.001)
Day 9				-0.004	-0.001	-0.002*
				(0.002)	(0.001)	(0.001)
Day 10				-0.005*	-0.002	-0.003**
				(0.003)	(0.001)	(0.002)
Day 11				-0.006**	-0.002	-0.004**
				(0.003)	(0.001)	(0.002)
Day 12				-0.006*	-0.002	-0.004**
				(0.003)	(0.002)	(0.002)
Day 13				-0.006*	-0.002	-0.004**
				(0.003)	(0.001)	(0.002)
Day 14				-0.006*	-0.002	-0.004*
				(0.003)	(0.002)	(0.002)
Day 15				-0.007*	-0.002	-0.005**
				(0.004)	(0.002)	(0.002)
Fixed effects?	no	no	no	no	no	Event time
Ν	150	150	150	900	1,350	2,250
R^2	0.041	0.038	0.076	0.136	0.065	0.055

Table 11: Regressions of cumulative abnormal turnover for equity around email recommendations, each email recommendation is an event. Abnormal turnover is defined as (turnover/normal turnover)-1, where normal turnover is the average turnover in the year before the each event and it is accumulated starting on day 1, the first trading day after the email recommendation. Columns labeled "Cross section" corresponds to regressions where the dependent variable is the cumulative abnormal turnover of the 50 largest stocks in the Santiago stock market in the event dates marked on the column head. 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. Return volatility is the standard deviation of the returns. Columns labeled "Sorted by size" correspond to pooled regressions of the cumulative abnormal turnover of Large and Small stocks for all event dates and events on event time dummies, where "Day t" is a dummy for the days that correspond to event time t for any of the events. Large stocks are the 10 largest stocks in Santiago's stock market, small stocks are the bottom 10 stocks among the 50 largest stocks. The last column is a pooled regression of the cumulative abnormal turnover of all stocks on a full set of event time dummies and the interaction between the event time dummies and a dummy for large stocks, we report the coefficients for these interactions. Note: Standard errors: robust in columns 1-3, clustered by event day in each event in columns 4-6. *** p < 0.01, ** p < 0.05, * p < 0.1.

Variables	(Cross sectio	on	Sort	ed by size	Large - Small
Variables	Day 5	Day 8	Day 10	Large	Small	
ln Mkt cap	0.320	0.671**	1.001**			
	(0.214)	(0.340)	(0.411)			
B/M	0.403	0.395	0.227			
	(0.350)	(0.477)	(0.579)			
MOM	0.582	1.164	1.646			
	(0.732)	(0.989)	(1.161)			
Ret Vol	-0.569	-0.966	-3.506			
5	(2.175)	(2.994)	(3.644)		- -	
Day 1				0.240**	-0.047	0.287***
				(0.116)	(0.102)	(0.110)
Day 2				0.361*	-0.038	0.399**
				(0.184)	(0.193)	(0.196)
Day 3				0.422	-0.182	0.604*
				(0.266)	(0.259)	(0.346)
Day 4				0.496^{*}	-0.096	0.591
				(0.278)	(0.325)	(0.425)
Day 5				0.569^{*}	0.004	0.565
				(0.324)	(0.419)	(0.586)
Day 6				0.821*	0.076	0.745
				(0.442)	(0.440)	(0.682)
Day 7				0.896^{*}	-0.110	1.006
				(0.533)	(0.496)	(0.809)
Day 8				1.173^{*}	-0.111	1.284
				(0.645)	(0.517)	(0.894)
Day 9				1.421*	-0.098	1.519
				(0.762)	(0.581)	(1.020)
Day 10				1.833^{**}	-0.090	1.923^{*}
				(0.794)	(0.673)	(1.119)
Day 11				2.168^{**}	-0.095	2.263^{*}
				(0.867)	(0.758)	(1.255)
Day 12				2.329^{**}	0.225	2.104
				(0.934)	(0.815)	(1.320)
Day 13				2.326**	0.170	2.156
				(1.019)	(0.867)	(1.442)
Day 14				2.371**	0.133	2.238
-				(1.092)	(0.987)	(1.583)
Day 15				2.502**	0.215	2.287
÷				14(1.169)	(1.018)	(1.687)
Fixed effects?	no	no	no	no no	no	yes
Ν	664	662	660	2,250	2,162	4,412
R^2	0.004	0.007	0.012	0.029	0.001	0.014

Table 12: Regressions of cumulative abnormal turnover government bonds around email recommendations, each email recommendation is an event. Abnormal turnover is defined as (turnover/normal turnover)-1, where normal turnover is the average turnover in days t - 5 to t - 1. Abnormal turnover is accumulated starting on day 1 because it corresponds to the first trading day since the email recommendation is sent. Columns labeled "Cross section" corresponds to a regression where the dependent variable is the cumulative abnormal turnover of the most representative Chilean government bonds in the event dates marked on the column head. Duration corresponds to the duration of each type of bond in the corresponding date. Nominal dummy takes a value of 1 for peso denominated bonds and 0 for (lagged) inflation indexed ones. Columns labeled "Sorted by maturity" correspond to pooled regressions of the cumulative abnormal turnover of Long and Short bonds for all event dates and events on event time dummies, where "Day t" is a dummy for the days that correspond to event time t for any of the events. 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 last column is a pooled regression of the cumulative abnormal turnover of all bonds on a full set of event time dummies and the interaction between the event time dummies and a dummy for long bonds, we report the coefficients for these interactions. Note: Standard errors: robust in columns 1-3, clustered by event day in each event in columns 4-6. *** p < 0.01, ** p < 0.05, * p < 0.1.

Variables	Cr	oss section		Sorted b	y maturity	Long - Short
(aritabiob	Day 5	Day 8	Day 10	Long	Short	Long Short
Duration Nominal dummy	47.122^{**} (19.357) 2.139	59.739^{**} (28.908) 2.564	83.435^{**} (37.864) 4.425			
i toiminai aaming	(1.393)	(2.202)	(2.896)			
Day 1				1.316***	0.645**	0.672^{*}
Day 2				(0.382) 2.163^{***} (0.526)	(0.252) 1.231^{***} (0.422)	(0.400) 0.932 (0.666)
Day 3				(0.550) 3.384^{***}	(0.422) 1.866^{***}	(0.000) 1.517^*
Day 4				(0.646) 4.695^{***}	(0.621) 2.515^{***}	(0.830) 2.179^{**}
Day 5				(0.982) 5.803^{***}	(0.812) 3.280^{***}	(1.035) 2.523^{*}
Day 6				(1.226) 6.596^{***} (1.470)	(1.008) 4.019^{***} (1.101)	(1.411) 2.578 (1.600)
Day 7				(1.479) 7.356^{***}	(1.121) 4.985^{***} (1.200)	(1.689) 2.371 (1.072)
Day 8				(1.664) 7.913^{***}	(1.389) 5.947***	(1.972) 1.966
v				(1.808)	(1.711)	(2.163)
Day 9				9.339^{***}	6.937^{***}	2.402
Day 10				(2.173) 10.570^{***}	(2.061) 7.893^{***}	(2.583) 2.677
Day 11				(2.403) 11.416***	(2.347) 8.320***	(2.888) 3.095
				(2.641)	(2.435)	(3.149)
Day 12				12.611***	8.866***	3.745
Day 13				(2.829) 13.092^{***}	(2.590) 9.438^{***}	(3.177) 3.654
Day 14				(3.016) 13.646^{***}	(2.761) 10.606^{***}	(3.322) 3.040
Day 15				(3.196) 13.888^{***} (3.330)	(2.998) 11.418*** (3.256)	(3.482) 2.470 (3.541)
				(0.008)	(0.200)	(0.041)
Fixed effects?	no 150	no	no	no	no 1.250	Event time
R^2	$150 \\ 0.061$	$150 \\ 0.040$	0.046	$900 \\ 0.248$	$1,350 \\ 0.177$	0.061

Table 13: Regressions of cumulative abnormal number of trades of government bonds around email recommendations, each email recommendation is an event. Abnormal number of trades is defined as (number of trades/normal number of trades)-1, where normal number of trades is the average number of trades in days t-5 to t-1. Abnormal number of trades is accumulated starting on day 1 because it corresponds to the first trading day since the email recommendation is sent. Columns labeled "Cross section" corresponds to a regression where the dependent variable is the cumulative abnormal number of trades of the most representative Chilean government bonds in the event dates marked on the column head. Duration corresponds to the duration of each type of bond in the corresponding date. Nominal dummy takes a value of 1 for peso denominated bonds and 0 for (lagged) inflation indexed ones. Ln Amount Outstanding is the log of the outstanding value of all bonds of each type. Columns labeled "Sorted by maturity" correspond to pooled regressions of the cumulative abnormal number of trades of Long and Short bonds for all event dates and events on event time dummies, where "Day t" is a dummy for the days that correspond to event time tfor any of the events. 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 last column is a pooled regression of the cumulative abnormal number of trades of all bonds on a full set of event time dummies and the interaction between the event time dummies and a dummy for long bonds, we report the coefficients for these interactions. Note: Standard errors: robust in columns 1-3, clustered by event day in each event in columns 4-6. *** p < 0.01, ** p < 0.05, * p < 0.1.

Variables	Cı	coss section		Sorted	by maturity	Long - Short
Variableb	Day 5	Day 8	Day 10	Long	Short	Long Short
Duration	28.342*	35.798*	52.211*			
	(15.763)	(21.076)	(27.615)			
Nominal dummy	0.501	-0.219	0.395			
	(1.462)	(2.081)	(2.627)			
Ln Amount	-0.893	-1.906	-1.974			
Outstanding	(1.653)	(2.179)	(2.737)			
Day 1				0.884^{***}	0.289^{**}	0.595^{*}
				(0.323)	(0.113)	(0.311)
Day 2				1.680^{***}	0.381^{**}	1.299^{**}
				(0.522)	(0.157)	(0.540)
Day 3				2.312^{***}	0.560^{**}	1.752^{**}
				(0.650)	(0.280)	(0.699)
Day 4				3.031^{***}	0.966^{**}	2.065^{***}
				(0.854)	(0.405)	(0.788)
Day 5				3.657^{***}	1.319^{***}	2.338^{**}
				(1.015)	(0.487)	(0.933)
Day 6				4.050^{***}	1.568^{***}	2.481^{**}
				(1.126)	(0.595)	(1.016)
Day 7				4.463^{***}	1.971^{**}	2.492^{**}
				(1.200)	(0.765)	(1.058)
Day 8				5.156^{***}	2.615^{***}	2.541**
				(1.382)	(0.952)	(1.142)
Day 9				5.985^{***}	2.968^{***}	3.017^{**}
				(1.655)	(1.081)	(1.383)
Day 10				6.828***	3.360***	3.468**
				(1.910)	(1.257)	(1.583)
Day 11				7.256^{***}	3.522^{***}	3.733**
				(2.054)	(1.274)	(1.758)
Day 12				8.214***	3.724^{***}	4.490**
				(2.257)	(1.340)	(1.899)
Day 13				8.735***	3.834^{***}	4.901**
				(2.460)	(1.433)	(2.053)
Day 14				9.378^{***}	4.237**	5.141**
				(2.657)	(1.631)	(2.124)
Day 15				9.663***	4.728**	4.936^{**}
				(2.813)	(1.875)	(2.144)
Fixed effects?	no	no	no46	no	no	Event time
Ν	150	150	150	900	$1,\!350$	2,250
R^2	0.046	0.041	0.048	0.199	0.104	0.061

Table 14: AFP Modelo. 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 email recommendation dummies 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.

		Pa	nel (a)	
		% of Yo	ung Investors ((below 35 yrs)
	AFP	Fund A	Fu	nd E
	MODELO	94%	5	3%
	CAPITAL	63%	2^{2}	4%
	CUPRUM	50%	19	9%
	HABITAT	66%	2'	7%
	PLANVITAL	64%	40	0%
	PROVIDA	69%	2	5%
		Pa	nel (b)	
			Dependent Va	ariable: Fund Flows $(\%)$
Variables	5		Fund A	Fund E
Email to	wards A		0.0404^{***}	-0.0187
			(0.014)	(0.032)
Email to	wards A X Mode	elo AFP	0.0780^{**}	-0.0719*
			(0.029)	(0.036)
Email to	wards E		-0.0372***	0.1627^{***}
			(0.010)	(0.041)
Email to	wards E X Mode	elo AFP	-0.1046***	0.0529
			(0.037)	(0.043)
Ν			225	227
R^2			0.689	0.534

sility. In panel (a) the dependent variable is the CAR of all stocks in the event day indicated	dent variable is the monthly return volatility of the stocks in the sample. Pressure from fund	w to fund A on month t times the weight of stock i held in fund A's portfolio in month $t-1$	neutum is the cumulated return between months $t-12$ and $t-2$. Market cap is the log of	's stock exchange measured on June of each year. B/M is book to market ratio measured in	corresponds to the average turnover of the past 12 months. Standard errors are clustered by	ed effects and time fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.	
Table 15: Noise trading and excessive volatility. In panel (a) the dependent	in the column head. In panel (b) the dependent variable is the monthly retu	A is defined as the absolute value of the flow to fund A on month t times the	divided by the market cap of stock i . Momentum is the cumulated return	the market value of the stocks in Santiago's stock exchange measured on Ju	December of the previous year. Turnover corresponds to the average turnov	month, and all regressions include stock fixed effects and time fixed effects.	

	Panel (a)	CAR in s	pecific ev	ent dates	Panel ((b) Monthly	r Return Vo	olatility
	Day 1	Day 3	Day 5	Day 8	(1)	(2)	(3)	(4)
Pressure Fund A	1.709^{***}	3.306	1.196	5.781^{**}	0.741^{***}	0.755^{***}	0.761^{***}	0.712^{***}
(absolute value)	(0.363)	(2.179)	(1.594)	(2.679)	(0.274)	(0.275)	(0.274)	(0.242)
ln Mkt cap	0.000	-0.001	-0.002	-0.003		-0.000	-0.001	-0.000
	(0.001)	(0.002)	(0.002)	(0.002)		(0.000)	(0.000)	(0.000)
$\rm B/M$	0.000	-0.003	-0.001	-0.003		-0.000	-0.000	-0.000
	(0.001)	(0.002)	(0.002)	(0.004)		(0.000)	(0.000)	(0.000)
MOM	-0.002	0.001	0.005	0.003		0.001^{**}	0.001^{**}	0.001^{*}
	(0.007)	(0.008)	(0.010)	(0.017)		(0.000)	(0.000)	(0.000)
Turnover	-0.039	-0.131	-0.129	-0.322			0.049^{**}	
	(0.082)	(0.179)	(0.114)	(0.280)			(0.021)	
Ret Vol_{t-1}								0.349^{***}
								(0.020)
N	617	617	616	614	6,987	6,987	6,915	6,987
R^{2}	0.227	0.219	0.175	0.474	0.504	0.505	0.503	0.566
# of x-sections	14	14	14	14	72	72	72	72