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Pension Funds and Capital Market Development

How Much Bang for the Buck?

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Abstract

This paper studies the relation between institutional investors and capital market development by analyzing unique data on monthly asset-level portfolio allocations of Chilean pension funds between 1995 and 2005. The results depict pension funds as large and important institutional investors that tend to hold a large amount of bank deposits, government paper, and short-term assets; buy and hold assets in their portfolios without actively trading them; hold similar portfolios at the asset-class level; simultaneously buy and sell similar assets; and follow momentum strategies when trading. Although pension funds may have contributed to the development of certain primary markets, these patterns do not seem fully consistent with the initial expectations that pension funds would be a dynamic force driving the overall development of capital markets. The results do not appear to be explained by regulatory restrictions. Instead, asset illiquidity and manger incentives might be behind the patterns illustrated in this paper.

This paper—a product of the Growth and the Macroeconomics Team, Development Research Group—is part of a larger effort in the department to understand financial development. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at craddatz@worldbank.org and sschmukler@worldbank.org.

Pension Funds and Capital Market Development: How Much Bang for the Buck?

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1. Introduction

Institutional investors have become increasingly important for both asset management and the development of financial systems. In fact, institutional investors are likely among the most important conduits of private and public savings, supplying capital for firms and countries to grow.[1] Among institutional investors, privately-managed, defined-contribution pension funds (henceforth pension funds) have played a crucial role across countries.[2] They have gained popularity as countries decided to shift away from publicly administered, pay-as-you-go, defined-benefit (DB) pension systems towards systems that rely mainly on mandatory, privately administered, defined-contribution (DC) pension funds. They have become popular even at the corporate level, where changes in the pension systems have entailed a shift away from defined-benefit towards defined-contribution schemes to transfer risk from corporations to individuals.

One key motivation for countries to reform their pension systems has been the expectation that these pension funds would play a dynamic role in the development of capital markets, fostering private sector savings and reducing the cost of capital for corporations, in the context of a broader strategy to achieve more developed, market-oriented financial systems.[3] Since pensioners save for the long run, pension funds (unlike other institutional or retail investors) are expected to be able to provide long-term financing to domestic corporations (fundamentally), as well as governments. Moreover, pensioners (by law) provide a steady flow of funds for many years to pension funds, enabling the latter to be a stable source of capital. Importantly, since pensioners are required to hold their investments in at least one pension fund until retirement, this gives stability to the system as a whole. Furthermore, given their size and commission fees, pension funds should be able to professionally manage the asset allocation, diversify risk appropriately, and overcome problems of asymmetric information and transaction costs

[1] For more on the relation between institutional investors and the development of the financial sector, see Vittas (1999), Reisen (2000), Blommestein (2001), and Davis and Steil (2001). For more on the link with economic growth, see Levine and Zervos (1996) and Levine (1997).
[2] Davis (1995) argues that increases in the holdings of pension funds (through a pension reform, for example) improve the depth of capital markets since they invest in long-term and riskier assets. Impavido and Musalem (2000) argue that pension funds also increase innovation, competition, and efficiency of capital markets. Impavido et al. (2003) find that the institutionalization of savings increases the depth of stock and bond markets and in some cases improves stock market liquidity.
[3] See Piñera (1991), Vittas (1995), and de la Torre and Schmukler (2006), among others.

that pervade financial markets. Also, given that pension funds face the regulatory requirement to allocate a large fraction of their capital domestically and given the large size of their capital, they are expected to invest in a broad range of domestic assets and diversify risk as much as possible within the country. Therefore, relative to other institutional investors, pension funds are thought to be the ones which contribute the most to the development of domestic capital markets.[4]

With these expectations in mind, many countries have reformed their pension fund systems. The first country to embrace the new pension fund model was Chile in May 1981, by replacing the public pension system with a DC pension system.[5] Many developed countries have followed suit and introduced substantial changes to their pension systems. For example, the UK moved towards a multi-pillar pension system through its 1986 Social Security Act (implemented in 1988) by allowing the creation of DC pension funds and providing incentives for people to abandon the DB system, in anticipation of a potential strain on public resources when the baby-boomer generation retired.[6] In Sweden, legislation was passed in June of 1994 (and implemented during 1995) to modify the pension system from a pay-as-you-go DB system towards a second-pillar system that includes a voluntary DC system.[7,8] In the US, proposals to reform the social security system have also been recurrently considered. Following Chile's example, many Latin American countries adopted similar reforms during the 1990s (but maintained a mixed system of both public and private pensions). These include Argentina, Bolivia, Colombia, Costa Rica, the Dominican Republic, El Salvador,

[4] Catalán et al. (2000) argue that contractual savings institutions (pension funds and life insurance companies) have a more important role in the development of capital markets compared to other investors, such as banks and open-end mutual funds. The authors claim that since contractual savings institutions have long-term liabilities on their balance sheets, they have a "natural advantage" in financing long-term investment projects relative to banks and open-end funds that have mainly short-term liabilities.

[5] The proposal for the new system was presented in 1980 and was actually implemented during 1981. For more details on Chile's reform, see De Mesa and Mesa-Lago (2006).

[6] See Disney and Emmerson (2005) for more details on UK's pension system reform. Note that the UK has continually introduced changes to its pension system over the past years, with major reforms taking place in 1995, 2000, 2004, and 2007.

[7] Sweden replaced its pay-as-you-go defined-benefit system with a pay-as-you-go notional defined contribution (NDC) system and an advanced-funded second pillar with privately managed individual accounts. For more on the Swedish pension reform, see Palmer (2000).

[8] Pension systems with a multi-pillar framework consist of: (i) the first pillar: a publicly managed, tax-financed pension system; (ii) the second pillar: a privately managed, funded scheme (defined-contribution pension funds); and (iii) the third pillar: voluntary retirement savings. Some countries maintain a first-pillar or second-pillar scheme instead of the full multi-pillar scheme.

Mexico, Peru, and Uruguay.[9] Moreover, many transition economies, including Hungary, Kazakhstan, Lithuania, Poland, and Slovakia, also adopted Chilean-style pension reforms.[10]

As a result of the reforms implemented across countries, the assets managed by pension funds have become substantial. In Chile, for example, pension fund assets reached 59 percent of GDP at the end of 2005, growing at an average annual rate of 46 percent between the inception of pension funds in 1981 and 2005.[11] In other countries that implemented reforms more recently, pension fund assets have also increased importantly, although their absolute levels as of 2005 were smaller and rarely exceeding 20 percent of GDP.[12]

By accumulating large private savings, pension funds have become important players in domestic capital markets. In a relatively mature system like the Chilean one (with an important presence of insurance companies and mutual funds), pension funds held around ten percent of equity market capitalization (which according to some estimates corresponds to around 28 percent of free-float), 60 percent of outstanding domestic public sector bonds, and 30 percent of corporate bonds' capitalization in 2004. In other, less mature systems, the participation in domestic equity and corporate debt markets is smaller, but certainly increasing.[13] Moreover, these funds may also become relevant international investors as the regulatory restrictions to invest abroad progressively fade.[14]

Despite the initial expectations, the actual impact that the increasing prominence of pension funds has had on the development of local capital markets is still subject to

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[9] See Queisser (1998), De Ferranti et al. (2002), and Gill et al. (2005).

[10] See Rutkowski (1998, 2002). Also, Holzmann and Hinz (2005) provide a detailed description of the pension reforms in developing countries by region, covering Central Asia, Central and Eastern Europe, Latin America and the Caribbean, Sub-Saharan Africa, and South Asia.

[11] See De Mesa and Mesa-Lago (2006).

[12] These countries include Argentina, Colombia, Costa Rica, the Dominican Republic, El Salvador, Hungary, Mexico, Poland, and Uruguay.

[13] Although pension funds in most Latin American countries (with the exception of Chile, the Dominican Republic, and Peru) remain concentrated on government securities, there has been an overall improvement in portfolio diversification between 1999 and 2006. See Dayoub and Lasagabaster (2007).

[14] For instance, foreign investments of Chilean pension funds reached 30 percent of their total assets in December 2005, a record level throughout the entire 1996-2005 period (having started at 0.3 percent). This corresponds to 18 percent of Chilean GDP or 20 billion US dollars (at the December 2005 exchange rate). See Dayoub and Lasagabaster (2007) for a detailed comparison of Latin America's pension reforms in the 1990s and an update on pension fund participation in financial markets.

debate. Some authors argue that pension funds foster the deepening of domestic equity and debt markets through their demand for investment instruments and their effect on corporate governance, and that they add to the liquidity of these markets through their trading activity (Davis, 1995; Vittas, 1995, 1999; Catalán, 2004; Catalán et al., 2000; Lefort and Walker, 2000, 2000a, 2002b; Corbo and Schmidt-Hebbel, 2003; and Andrade et al., 2007). Others maintain that pension funds do not contribute as expected to the development of capital markets, and are not investing pensioners' savings optimally (Arrau and Chumacero, 1998; Zurita, 1999; IMF and World Bank, 2004; Yermo, 2005; Olivares, 2005; Berstein and Chumacero, 2006; and The Economist, 2008).

This paper aims to shed light on the debate of how pension funds affect capital market development, especially that of secondary markets, by providing a systematic analysis of the pension fund investment behavior and the factors that constrain it. This is done by: (i) studying in detail, at the micro level, how pension funds invest; and (ii) discussing how their strategies vary with factors that can significantly restrict the funds' ability to allocate assets and to contribute to local capital market development. In particular, the factors analyzed in this paper are: regulations, managers' incentives, and liquidity.

We analyze the investment behavior of pension funds using a unique and rich dataset that contains the detailed portfolios of the universe of pension funds in Chile at a monthly frequency for ten years (1996 to 2005). This dataset is matched with a separate dataset containing the returns of each instrument included in these portfolios. The combined and cleaned dataset contains 7,501,210 observations, with information on the holdings and returns of 104,789 different securities, for up to 57 pension funds. All the information is analyzed by taking into account the regulatory framework in which funds operate and its changes over time. These regulations include macro and micro restrictions such as the list of investable assets.

We use these data to address a series of questions regarding pension fund portfolio allocations and trading strategies. The questions related to portfolio allocations that guide our research are: Where do pension funds invest (both in terms of asset classes, type of assets, country origin, and maturity)? To what extent do pension funds diversify their holdings? How do pension fund portfolios vary with different degrees of regulatory restrictions? The questions related to pension fund trading behavior are: How actively do pension funds trade and do they buy/sell the same assets simultaneously? Is their trading activity associated with variations in returns? Have there been changes over time in their trading behavior, perhaps determined by regulatory modifications? Is their trading pattern different across asset classes? Many of these questions are already answered in the current paper, while others remain material for future research.

To address these questions, we use different measures that characterize pension fund portfolios and trading strategies. These measures are computed both at the level of the pension fund administrators or PFAs (with each managing five funds since September 2002) and at the level of pension funds. We look at indicators of portfolio similarity across funds. We also construct measures of herding, which capture how pension funds invest. These measures can shed light, among other things, on how regulatory changes and competition among pension funds affect pension fund holdings. We also compute measures of turnover of pension fund portfolios. An active participation of pension funds in the markets could provide secondary market liquidity and foster capital market development. On the other hand, holding instruments for a long time, for example up to maturity, reduces market liquidity which is vital for the emergence of new instruments, for capital raising activity, and for the necessary well-functioning of secondary markets.[15] Additionally, we compute measures of momentum trading strategies carried out by pension funds. The presence of these strategies is typically associated with market volatility, as funds buy assets with positive returns and sell assets with negative returns, perhaps making markets more pro-cyclical. At the same time, momentum trading by funds might be consistent with investing at short horizons, such as selling long-term bonds when their prices fall, and perhaps inconsistent with long-term strategies that would maximize pensioners' returns. In other words, fund managers might be too sensitive to short-term asset price changes.[16]

The main results from this analysis can be summarized as follows. First, pension funds hold a large fraction of their portfolios in assets that can be easily liquidated, namely, bank deposits, government bonds, and more generally short-term instruments

[15] See Broner et al. (2006, 2007).
[16] Miles (1993) finds evidence in favor of the "short-termism" hypothesis in the UK equity market, arguing that large institutional investors invest sub-optimally in long-term investments.

among fixed-term securities. This is not explained by the lack of investable instruments since pension funds do not even invest in all of the available and pre-approved assets. Second, our results indicate that funds do indeed tend to hold similar portfolios at the asset-class level and herd in their investment decisions, especially among their investments in domestic equities, domestic corporate bonds, and quotas of foreign mutual and investment funds. Third, we find relatively low turnover measures; that is, pension fund administrators infrequently change their positions. Moreover, once a PFA buys a fixed-income instrument, it holds it up to maturity in almost all cases. This evidence of a buy-and-hold strategy is consistent with the evidence on the number of active trades, which is surprisingly low.[17] Thus, our broad characterization suggests that, to an important extent, pension fund administrators do not actively manage their positions as a trading strategy. Fourth, we compute several momentum statistics (widely used in the finance literature) that measure the correlation between the change in a fund's position in a given asset and that asset's past performance. The results indicate that there is a significant fraction of funds whose trading follows a momentum strategy, that is, they buy past winners and sell past losers (in terms of asset returns). This type of strategy seems particularly important for certain asset classes, especially government paper, domestic equities, and quotas of foreign investment and mutual funds. We find no significant evidence of contrarian trading (buying past losers and selling past winners) at any level, nor do we find evidence that momentum trading is the main cause of the herding observed in domestic assets such as equities. Furthermore, we find some evidence that liquidity considerations might play a role when comparing strategies across asset classes with different aggregate levels of liquidity. Fifth, most of the patterns of trading behavior mentioned above do not change significantly around regulatory changes in the band of minimum return (that PFAs must achieve for their overall portfolios) or across fund types facing different regulatory return requirements. This suggests that regulatory restrictions on returns are unlikely to be the main cause of trading patterns such as herding. However, regulations on foreign holdings notably affect pension fund investments over time, and trading behavior experiences a change after the introduction

[17] A small fraction of assets (11 percent) is traded by any PFA in a typical period. Moreover, most assets that experience some trading are traded by only one PFA, only three percent of assets are traded by more than one PFA, and only one percent of assets are traded by more than half of PFAs.

of the multi-fund system with a significant decline in the degree of herding and momentum across PFAs. Finally, the onset of the Russian crisis in 1998 coincides with a temporary decline in herding and an increase in turnover, which suggests that the turmoil in financial markets associated with this episode disrupted the trading strategies of Chilean PFAs.

In sum, putting all this evidence together, our results depict pension fund administrators as large and important institutional investors that hold a large amount of bank deposits, government paper, and short-term assets, buy and hold assets in their portfolios without actively trading them, tend to simultaneously buy and sell similar assets and hold similar portfolios, and when trading tend to follow momentum strategies. These patterns are not driven just by regulations and do not seem fully consistent with the initial expectations that pension funds would be a dynamic force stimulating the overall development of capital markets, especially that of secondary trading markets. This is not to say that pension funds do not contribute to market development. Our evidence has little to say about the role of pension funds on the development of primary markets that are crucial for firms' access to non-intermediated funds. However, our results indicate that expectations about the role of pension funds on the overall development of capital markets might need to be revisited. While pension funds may ease the access of some firms to funds through equity or bond issuances, they seem less likely to contribute to market trading activity, price formation, or to the provision of funds at longer maturities. Still, much more research would need to be done to understand how pension funds behave; in particular, one would need to compare pension funds with other institutional investors in Chile and abroad. (As a first step in this direction, see Opazo et al., 2008, for a study on the maturity structure of different types of institutional investors in Chile.)

In our discussion of the results we highlight those aspects that shed some light on the three factors that might constrain pension funds' investment decisions. First, pension funds are heavily regulated both to protect pensioners' assets and to foster domestic capital market development, which might create a trade-off between what funds find profitable and the more general objectives that regulators face. Second, the incentives that pension fund managers face might lead to herding behavior and short-term investments. Managers are typically evaluated by investors against deviations from a benchmark, which might induce them to herd. Furthermore, regulations might promote herding by establishing bands within which returns across funds have to lie. In addition, there is a tension between the need to generate high long-term returns, on the one hand, and the need of fund managers to yield acceptable short-term returns to keep attracting investors over time, on the other hand. This is compounded by the fact that, while pension funds are thought to be long-term investors, they are purely asset managers, not asset-liability managers. These incentives on pension fund asset allocation might be important and have been typically overlooked by the literature.[18] Finally, as pension funds become large relative to the domestic capital market, they are more likely to influence returns with their trades, affecting their ability to buy and sell illiquid securities. Therefore, the degree of domestic market development (or underdevelopment) may shape how funds invest. Namely, it is not just that pension funds affect capital markets; rather, there is a two-way relation between pension funds and capital market development. As discussed in the Conclusions, more work needs to be done to understand the relative importance of these factors in shaping pension funds' investment behavior.

The rest of the paper is structured as follows. Section 2 briefly summarizes the main features of the Chilean pension system. Section 3 describes the data. Section 4 characterizes pension fund portfolios. Section 5 analyzes the investment behavior of pension funds. Section 6 concludes. The Appendix provides some more detailed information.[19]

2. The Chilean Pension Fund System

2.1. Brief Account of the System Evolution

In 1980, Chile decided to reform its pension fund system with the objective of overcoming the inherited fiscal burden of the old regime, reducing the public sector's role in economic affairs, reducing taxes and fostering capital market development, and

[18] Asset-liability managers, unlike pure asset managers, might have more incentives to seek returns that are consistent with their long-term liabilities. This would be the case for annuity providers and defined-benefit pension funds. See de la Torre, Gozzi, and Schmukler (2007).

[19] Additional background information on the Chilean pension system and a detailed description of the cleaning and merging of the datasets are available upon request to the authors.

correcting the inequalities and distortions of the old regime.[20,21] In May 1981, the pension law replaced the pay-as-you-go system with a fully-funded capitalization system based on individual accounts operated by the private sector and regulated by the Superintendency of Pensions (*Superintendencia de Pensiones*, SP).[22] At the time of the transition, contributors were given the choice of remaining in a national state-run DB system or transferring to the new individual account system and having their past service valued via former pension system bonds (*bonos de reconocimiento*), which would come due at retirement. All new entrants to the wage workforce would be automatically enrolled in the new scheme and would select a pension fund administrator (PFA) to manage their accounts, but could not select individual investments themselves.

During the first ten years of the system, each PFA managed a unique fund in which all contributions were invested according to a set of quantitative regulations that we describe below, thus offering no choice to the individuals in terms of risk-return combinations. The set of choices was expanded in March 2000 by the introduction of a new fund type (Fund 2), and in August 2002 by the implementation of the multi-fund scheme in which all PFAs started offering a set of five different funds to their contributors (Funds A to E). These funds are each subject to different restrictions on their asset allocation and, therefore, offer a different risk-return combination, with Fund A (Fund E) being the most (least) risky. Depending on their age and gender profile, contributors can choose among a subset of these five funds.

2.2. Investment Regulations

Chilean pension fund administrators invest in different funds subject to a large set of quantitative restrictions that are defined by law and that specify how much pension fund administrators are allowed to invest in specific instruments.[23] Pension funds can

[20] The previous Chilean social security system began operating in 1924 based on collective capitalization funds. As the system matured, it was expected that growing obligations would be met by drawing on these funds and increasing contributions made by active workers, but these funds were poorly managed and, as a result, the system started operating with financial difficulties and relying increasingly on the government's support to meet its obligations. By the early 1970s, the system as a whole was running a substantial deficit.

[21] For more details, see Larraín (1993), Edwards (1996), and SP (2003).

[22] Until 2006, 41 amendments were made to the pension law (20 of which were approved during the 1980s).

[23] For a summary of the pros and cons of adopting quantitative limits, see Candia (1998).

only invest in financial assets listed in the pension law and traded in public offerings.[24] Within the bands established in the pension law, different investment limits are imposed on each fund type, with the objective of ensuring the appropriate yield and security according to the risk profile of each fund type.[25] These investment limits have been modified over time, incorporating quantitative and conceptual changes. Broad investment limits are defined across several dimensions: per instrument, per issuer, per group of instruments, and for issuers related to the PFA.

Additionally, pension funds are subject to a minimum return regulation that establishes that administrators are responsible for ensuring an average real rate of return over the last 36 months that exceeds either (i) the average real return of all funds minus two percentage points for Funds C, D, and E, and minus four percentage points for Funds A and B, or (ii) 50 percent of the average real return of all the funds, whichever is lower.[26,27]

After the introduction of the multi-fund scheme in August 2002, investment limits per instrument set by the central bank have not changed for domestic instruments but have been relaxed twice for foreign investments (an additional relaxation took place in August 2002). Limits on domestic fixed-income (variable-income) instruments gradually

[24] The issuers of these assets must be supervised by a government agency, such as the Superintendency of Securities and Insurance (*Superintendencia de Valores y Seguros*, SVS) and the Superintendency of Banks and Financial Institutions (*Superintendencia de Bancos e Instituciones Financieras*, SBIF) in the case of Chilean issuers, or their equivalent in other countries. In addition, the majority of these instruments must be approved by the Risk-Rating Commission (*Comisión Clasificadora de Riesgo*, CCR) – with a few exceptions including instruments issued or guaranteed by a central government or those issued by the Central Bank of Chile (*Banco Central de Chile*, BCC).

[25] These investment limits are fixed by the Central Bank of Chile (*Banco Central de Chile*, BCC) based on reports issued by the Superintendency of Pensions of Chile (*Superintendencia de Pensiones*, SP) and are always within the bands established in the pension law. The central bank sets investments limits through regulations named "Circulares" altering letter F (Pension Fund Administrators, Insurance Companies and Administrators of Unemployment Funds) of Chapter III (Rules for Operation, Intermediation and Control of the Financial System and Capital Market) of the Compendium of Financial Regulations.

[26] The average real rate of return to calculate the minimum return changed from 12 months to 36 months in October 1999.

[27] For this purpose, PFAs must keep a return fluctuation reserve equal to one percent of the value of each fund, which is used if the minimum return is not achieved. When the difference is not completely covered by this reserve or the administrator's funds, the state must provide for it. However, in this case or when the reserve is not restored after being used (in a 15-day period), the PFA's operating license can be revoked.

increase (decrease) as funds become less risky (i.e., when one moves from Fund A towards Fund E).[28,29]

3. Data

The data used in this paper were obtained from the Superintendency of Pensions of Chile (*Superintendencia de Pensiones, SP*) and consist of two datasets, containing information on holdings and on returns. When combined, we obtain a panel of all the portfolio investments of PFAs in operation, for each of their funds, during the period 1996-2005 at a monthly frequency, including information on returns.

The holdings dataset is structured as a panel with data on the price and quantity for every security held, by fund, per unit of time. We define a fund as a pair PFA/fund type (e.g., Fund C of PFA *Aporta* configures a single fund). After cleaning this dataset (one percent of observations were dropped from the original dataset), there are 7,501,210 observations, representing all securities held during each month by at least one fund. The dataset contains information on the holdings of 104,789 different securities, for up to 57 funds, at a monthly frequency from July 1996 to December 2005.

The data on returns consist of a panel containing a time series for the price, returns, dividends, and term to maturity (available depending on the nature of the asset) of each instrument. After the cleaning process, the dataset contains 5,467,959 observations from July 1996 to December 2005 (0.1 percent of observations were dropped from the original dataset).[30]

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[28] Fund A is the riskiest fund, having the lowest (highest) limits on domestic fixed-income (variable-income) instruments across the five funds. Fund E is the most conservative fund, having the highest limits on fixed-income instruments, the only instruments in which its assets are allowed to be invested. Limits on shares of domestic mutual funds are the same (five percent) for Funds A, B, and C, but the aggregate limit for shares of domestic mutual and investment funds gradually decreases – from 40 percent (Fund A) to 20 percent (Fund B) to ten percent (Fund C). For foreign investments, the limit is set at the PFA level and was relaxed twice during 2003 (becoming effective in May 2003 and March 2004). The maximum allowed by law is 30 percent of the value of all funds managed by a single PFA.

[29] Regarding limits for specific instruments, two of them address instruments that do not require the approval from the Risk-Rating Commission (*Comisión Clasificadora de Riesgo,* CCR) approval. For corporate stocks and shares of mutual and investment funds that do not require the CCR's approval, pension funds can invest either three percent (Funds A and B) or one percent (Funds C and D) of their assets. For foreign investments and other publicly traded securities that do not need such approval, the investment limit as a share of the pension fund's assets is one percent for Funds A, B, C, and D.

[30] Due to the lack of dividend information in our dataset for the year 2000, all the calculations presented in the paper are carried out using a measure of returns that does not include dividend information. Some estimates were computed with dividend information obtaining similar results.

As a first step, we cleaned both datasets, appending afterwards the information on returns to the holdings dataset. During the cleaning process we dropped duplicate entries, corrected the values of several variables, and generated an identifier variable for the securities in each dataset.[31]

After cleaning and merging the datasets we obtain a panel of 7,501,210 observations, corresponding to 104,789 securities, which are grouped in 56 different instrument types. While 54 of these instrument types each account for a 0.37 percent of the observations (on average), there are two types of instrument that represent 80 percent of all observations: the former pension system bonds (*bonos de reconocimiento*), which represent 43.71 percent of the data, and mortgage bonds (*letras hipotecarias*), which represent 34.60 percent of observations.[32] We then group these instrument types into 12 general asset classes, considering both former pension system bonds and mortgage bonds as separate asset classes due to their importance.[33]

4. Pension Fund Holdings

Pension fund administrators have become the largest institutional investors in Chile. This section briefly describes their relative importance in the Chilean capital markets, their broad patterns of asset allocation, and the concentration of their investments.

4.1. Pension Fund Size and Relative Importance

During the period 1996 to 2005 covered by our data, the number of PFAs operating in Chile decreased by two-thirds while the number of pension funds doubled. The number of PFAs decreased from 15 to six due to a series of mergers and acquisitions

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[31] Since each dataset contained a different set of identifier variables we could not generate a unique identifier variable for both datasets. Therefore, we initially merged both datasets by the name of the instrument and the price to establish a correspondence between both identifier variables, later merging the datasets a second time in order to recover additional information on returns.

[32] It is important to note that although former pension system bonds and mortgage bonds combined represent 80 percent of observations form the dataset, they only represent 16 percent of the total portfolio investments when considering the entire system for the 1996-2005 period, varying from a maximum portfolio share of 20 percent in 1996 to nine percent at the end of 2005.

[33] The 12 asset classes are: domestic corporate bonds, instruments of domestic financial institutions, quotas of domestic investment and mutual funds, government paper, domestic others, domestic equity, foreign fixed-income, quotas of foreign investment and mutual funds, foreign others, foreign equity, former pension system bonds, and mortgage bonds.

that mostly took place in the late 1990s (Figure 1).[34] The number of pension funds in the market has been proportional to the number of PFAs. Thus, from July 1996 to December 2005, the number of pension funds increased from 15 (one per PFA) to 30 (five per PFA).

Assets under pension fund management increased substantially from 1996 to 2005 both in absolute and relative terms (Figure 2). In 2005, pension funds managed around 38.3 billion Chilean pesos, an amount that was almost 2.5 times the 1996 value in real terms. As a share of GDP, assets managed by pension funds increased 1.6 times, from 37.4 percent in 1996 to 57.5 percent in 2005 (Figure 3). Since the creation of the multi-fund scheme in August 2002, Fund C, which is the continuation of the old Fund 1, has been the fund with the largest relative share of assets in the system. However, the relative participation of the two riskiest funds (Funds A and B) has been steadily increasing (Figure 4).[35]

The participation of Chilean pension funds in the markets for different instruments varies significantly. For fixed-income instruments, the average holding of bills and bonds by pension funds was around 65 percent of the total domestic debt during 2001-2005. For equities, it was 7.8 percent of the total domestic market capitalization, during 1996-2005, with a decreasing trend during this period (Figure 5). Moreover, relative to OECD countries and Colombia, the allocation was high in fixed-income instruments and low in equities (for a given level of pension fund assets as a share of GDP).[36] This might be explained by: (i) the high percentage of closely held shares, which in Chile averaged 64.7 percent during 2001-2005, and (ii) the relaxation of the

[34] Of the three largest Chilean PFAs, two of them – *Cuprum* and *Habitat* – have never merged with or acquired competitors, while the current PFA *Provida* results from three mergers between *Provida* and *El Libertador* in 1995, *Unión* in 1998, and *Protección* in 1999.

[35] The increasing importance of Funds A and B is due to: (i) SP's automatic allocation of contributors who do not choose a fund in which to deposit their monthly contributions to a specific fund, especially from November 2002 to November 2003, and (ii) the voluntary switching of accounts from more conservative to riskier funds as an attempt of younger affiliates to achieve higher returns (Figure 1). The automatic allocation works as follows: (i) contributors younger than 35 years old are assigned to Fund B, (ii) contributors older than 35 years old but younger than 55 (men)/50 (women) years old are assigned to Fund C, and (iii) contributors older than 55 (men)/50 (women) years old are assigned to Fund D. As of April 2007, about 68.6 percent of the system's 8.63 million affiliates had been automatically assigned by SP, of which 42 percent, 46 percent, and 12 percent were assigned to Funds B, C, and D, respectively.

[36] Source: OECD Global Pension Statistics and World Bank Financial Development Indicators (WDI).

investment regime over time, particularly regarding variable-income instruments and foreign assets.[37]

4.2. In Which Asset Classes Do Pension Funds Invest?

One striking feature of pension fund asset holdings is the proportion they invest in assets that can be easily liquidated, namely, bank deposits, government bonds, and more generally short-term instruments among fixed-term securities. For example, Figure 6 shows that PFAs hold a significant fraction of their portfolios in assets issued by financial institutions (mostly bank deposits) and government paper. Table 1 shows details by fund type. On average, for the entire period, Fund A (the riskiest one) holds almost 18 percent of its assets in bank deposits and government paper. As a benchmark, US equity mutual funds that invest internationally hold on average only 3.5 percent in "cash," typically money management instruments.[38] In the case of Fund E, this ratio jumps to 58 percent.

Figure 7 and Table 2 show that pension fund holdings are also tilted towards the short term. (See Opazo et al., 2008, for more on Chilean pension funds and short-termism.) Figure 7 shows the maturity schedule for all fixed-term instruments held by PFAs, averaged across the entire sample period and at the end of December 2005. When considering the whole period, 44.8 (24.2) percent of investments in fixed- term securities is held in instruments maturing within three (one) years. Table 2 shows the breakdown by fund type. Fund A holds 76 percent of its fixed-income securities in instruments with a term to maturity of up to three years, 60 percent up to one year, and 12 percent up to 30 days. At the other extreme, Fund E holds 59 percent of its fixed-income instruments in assets that have a term to maturity of up to three years and 24 percent up to one year.

Consistently with the bias towards fixed-term instruments documented above, asset allocation in the domestic market has been done mostly (about 75 percent) through investment in fixed-income instruments (Figures 8 and 9). The participation of corporate bonds in the portfolio of pension funds more than doubled between 2000 and 2005, coinciding with the tenfold increase in issuance of Chilean companies during this period, probably responding to falling domestic interest rates and regulatory changes (Braun and

[37] Closely held shares are the shares held by insiders of a firm, which are unlikely to be floated on the market and are thus unavailable to outside investors. For details, see Dahlquist et al. (2003). The source of the closely held estimate is the World Bank Financial Sector Development Indicators.
[38] See Didier et al. (2008).

Briones, 2006). For pension funds, this was an opportunity to take advantage of (corporate bond) returns that were 200 basis points higher than the returns of central government bonds and treasury bills (IMF and World Bank, 2004). The increase in the participation of domestic equity in the portfolio of pension funds coincides with both a rebound in the domestic equity market after the Russian Crisis of 1998 and the creation of the multi-fund scheme in 2002 (Figures 6 and 10).

The distribution of investments across asset classes for different funds is generally consistent with the objectives of the multi-fund scheme and is, to a great extent, in line with the quantitative investment regulations. The portfolio composition of Fund A, designed to offer the highest risk-return combination, effectively has the largest participation of both domestic equity and foreign instruments (mainly variable income). Fund E, the most conservative fund, has a portfolio exclusively composed of fixed-income instruments, particularly government paper and securities issued by domestic banks and other financial institutions. Even though the investment regulation is restrictive, pension fund administrators have some room to maneuver and have used it to expand the asset allocation of funds in variable-income instruments, particularly for Funds A and B. The portfolio composition of Fund C, the central fund, has remained mildly conservative after the beginning of the multi-fund scheme in 2002, with a small proportion of funds invested in equities (about ten percent) and large shares of fixed-income instruments. The portfolio composition of Fund D has remained conservative and stable since its creation in 2002 (Figure 11).

Despite the fact that asset allocations of different portfolio types are broadly consistent with the limits imposed by regulation, it is difficult to ascertain that these regulations are fully binding because of the large number of overlapping macro and micro regulations (for example, at the macro level the sum of the maximum investment limits on the different asset classes considered in the law is much higher than 100 percent so mechanically they cannot be all binding simultaneously). However, it is apparent that investment limits are binding for PFAs' investment in foreign assets, where the limit has been reached in various occasions. The gradual relaxation of the investment regime has been matched with an increasing participation of foreign variable-income instruments in their portfolio composition. (Figure 8) From July 1996 to December 2005, the percentage of assets of pension funds invested in the foreign sector increased 100 times, with allocation reaching the limit of 30 percent across funds per PFA at the end of the period.

In contrast with the emphasis on fixed-income assets among domestic assets, the majority of investments in foreign assets has been done through the holdings of quotas of foreign mutual and investment funds, particularly in Luxembourg, the US, and Ireland (Figure 12). Since 2000, the holdings of these instruments increased at the expense of foreign fixed-income instruments, coinciding with the continuous decline of interest rates in the US.

Holdings of quotas of mutual and investment funds have been considered variable-income in the current classification system, regardless of whether the fund is an equity or bond fund. Therefore, variable-income instruments represent a relatively high proportion of the portfolio of pension funds.[39]

When investing across asset classes, pension funds seem to have similar allocation strategies. For example, Figure 13 shows the allocation per asset class across PFAs in December 2005 for Fund C. The similarity of the portfolio shares in each asset class across PFAs is apparent. In fact, the differences across asset classes are much larger than the differences across PFAs for each asset class. This pattern is not particular of Fund C or of this specific month, but is repeated across fund types and time. This can be seen in Table 3 that summarizes the average distance across PFAs' portfolio shares across asset classes per fund type. For the entire period the average distance for Funds A, B, and C is about ten percent. This is about one-third of the distance that we would expect if funds allocated their assets randomly across asset classes.[40]

4.3. Investment Concentration

Chilean pension funds hold a large number of fixed-income instruments, but the bulk of them are bonds from the former pension system and mortgage bonds, which as a

[39] Variable-income assets accounted for 46.9 percent of the portfolio in December 2005 (of which about one-third were domestic assets and the rest were foreign assets). In 2003, shares of mutual and investment funds accounted for approximately 30 percentage points, out of the 38 percent of investments in variable-income instruments (IMF and World Bank, 2004). Still, the increasing holdings of foreign assets involve investments in foreign equity to a large extent.

[40] We compute the distance resulting from random allocations by simulating the portfolio shares across 12 asset classes of 1,000 funds, assuming that each share is independently drawn from a uniform distribution with support between zero and one (and normalizing the resulting sum to one after drawing). We compute the distance between each pair of vectors of shares and take the average of distances.

whole represent a minor fraction of the portfolio in terms of value (4.5 percent and 11.4 percent, respectively). Excluding these instruments, the most prevalent assets in terms of number of instruments are government bonds, assets from domestic financial institutions, and quotas of foreign investment and mutual funds. This can be seen in Figure 14, which shows the median number of instruments held per asset class across pension funds and PFAs during 1996-2006. The figure shows an increasing trend in all asset classes, stabilizing only after 2003. Therefore, the data do not show pension funds holding a stable number of instruments in their portfolios, but continuously absorbing a larger number of them. This is probably related to the low trading activity documented in the next section. The increasing trend is relatively similar across asset classes, with quotas of foreign investment and mutual funds experiencing a significantly faster growth in the number of instruments of around 50 percent during the period, most likely due to the relaxation of regulatory restrictions.

PFAs do not concentrate a majority of their portfolio in a small set of securities; for example, in December 2005 the average across PFAs of the C5 concentration index (the sum of the portfolio shares represented by the 5 instruments with the highest portfolio shares) ranged from eight percent for Fund A to 13 percent for Fund E. This is not surprising considering the regulatory restrictions that limit the fraction of the portfolio that can be invested in a particular security and the fraction of the security issuance that can be purchased by a PFA.[41] Our data do not allow us to determine precisely whether these micro-regulations are binding in any asset class, rather they only allow us to check whether restrictions associated with the share of an instrument in the total value of a portfolio is violated for some asset classes. As it turns out, these restrictions (associated with portfolio diversification issues) are typically not binding. Since the value of a PFA's portfolio under management is significant, restrictions on the fraction of a stock's shares outstanding or the fraction of the issuance of a given bond (i.e., those associated with control issues) are more likely to be binding.[42]

[41] It is somewhat surprising, however, that for Fund A, three domestic equities are systematically among the five securities with the largest portfolio shares: Endesa, Enersis, and Copec.

[42] Determining the relevance of these constraints requires gathering data on the amount of shares outstanding and the value of the issuance of various bonds, which is left for future research.

Probably the most interesting finding related to concentration is that PFAs do not seem to be allocating funds to all the assets to which they could, which leads us to question whether the potential gains from diversification are fully exploited. Table 4 shows the number of instruments approved by the Risk-Rating Commission (*Comisión Clasificadora de Riesgo*, CCR) in various asset classes for the period 2002-2005, and the fraction of approved instruments in which PFAs are investing. In all asset classes with available data, PFAs are investing in only a subset of the assets in which they could. For example, during this period they invest in between 65 to 72 percent of all the approved equity, and between 15 and 18 percent of all the approved foreign mutual funds. Although this may indicate that PFAs are foregoing opportunities for diversification, it can also be due to other reasons, for instance, a high degree of correlation between assets that does not compensate for incurring transaction costs. A first step in sorting out these alternative explanations can be done by determining the characteristics of the assets that PFAs include and exclude from their portfolios, which we leave for future research.

5. Pension Fund Investment Behavior

This section explores three aspects of trading behavior that have received attention in the mutual fund literature of developed countries: (i) whether funds follow each other in their decisions to buy and sell assets, which is typically labeled *herding behavior*, (ii) whether funds are active traders and adjust their positions frequently contributing to liquidity creation (i.e., whether the degree of turnover is high), and (iii) whether funds' investment decisions are correlated with past asset performance and therefore may potentially contribute to exacerbate market fluctuations (i.e., whether they are momentum traders). While examining each of these aspects we also look at whether crisis episodes or regulatory changes occurring during our sample period have consequences on the patterns of trading. Although as shown above the investment allocation of pension funds across asset classes is in line with quantitative regulatory restrictions, these restrictions do not constraint PFAs' trading activity. Therefore, the trading patterns of PFAs might shed additional light on whether these funds act as long-run investors and contribute to the development of capital markets.

5.1. Do Pension Funds Herd?

Anecdotal evidence suggests that Chilean pension fund administrators tend to follow similar investment strategies, such as buying and selling assets in block, which is typically referred to as *herding behavior*. This section tests for the presence of herding on the trading patterns of Chilean PFAs.

When computing herding measures, it is important to take into account the frequency and distribution of trades across asset classes. Table 5 summarizes the typical fraction of the universe of assets in PFA portfolios that are traded in a given month, both overall and by asset class. The overall results show that a small fraction of assets (11 percent) is traded in a typical month, and most of the time by only one PFA: only three percent of assets are traded by more than one PFA and only one percent of assets are traded by more than half of PFAs. These facts are inconsistent with a simplistic view of herding where there is significant trading and all traded assets are being simultaneously bought or sold by most PFAs. Instead, in our data there are typically few assets being traded, and most of this trading is carried out by single PFAs.

There is, however, important variation across asset classes: a majority of domestic equities and quotas of foreign investment and mutual funds are traded in a typical period and an important fraction of them by more than one PFA. Other standard asset classes that exhibit an important degree of trading are government bonds and foreign equity. On the other hand, there is a low degree of trading in former pension system bonds and in instruments from financial institutions that include time deposits that are not traded in secondary markets. Because of this heterogeneity, we focus on statistics per asset class instead of overall measures and stress that herding measures describe those cases in which PFAs are actively trading. Naturally, the herding measures are more relevant for the most traded assets.

The literature has built several measures to quantify herding and test for its presence. These measures focus on two aspects of trading similarity. First, whether funds simultaneously buy or sell the same assets in a given moment, which could be labeled *contemporaneous herding*, and, second, whether assets that are traded in a given period are more likely to be traded in subsequent moments, which could be labeled *dynamic herding*.

We measure the degree of contemporaneous herding using the approach of Lakonishok et al. (1992) which relies on the idea that when there is no herding the probability of buying has to be equal among assets. Therefore, a measure of the difference between the probabilities of buying across assets can be used to test the hypothesis of no herding. In particular, Lakonishok et al. (1992) define the herding statistic $H(i,t)$ as:

$$H(i,t) = \left| \frac{B(i,t)}{N(i,t)} - p(t) \right| - AF(i,t), \tag{1}$$

where $p(t)$ is the probability of buying any asset at time t, $B(i,t)$ is the number of funds that increase their holdings of asset *i* at time *t* (buyers), $S(i,t)$ is the number of sellers of asset *i* at time *t*, and $N(i,t) = B(i,t) + S(i,t)$ the number of funds active on asset *i* at time *t* (i.e., either buying or selling), and $AF(i,t)$ is an adjustment factor. Under the hypothesis that no herding occurs, the number of buyers $B(i,t)$ follows a binomial distribution with parameters $p(t)$ and $N(i,t)$, and the adjustment factor $AF(i,t)$ is the expected value of the first term under this hypothesis, which is positive because of the use of the absolute value. Therefore, if no herding occurs we should be unable to reject the null hypothesis that the herding statistic has a mean of zero.[43,44]

Table 6 reports our main results on contemporaneous herding, with each entry displaying the mean of the herding statistic for each asset class and its corresponding

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[43] The adjustment factor $AF(i,t)$ is $AF(i,t) = E\left(\left| p(i,t) - E[p(i,t)] \right|\right)$, where $p(i,t)$ is the probability of buying an asset *i* at time *t*. The proportion of all funds that buy during period *t* is used as a proxy for $E[p(i,t)]$, and due to the assumption that the number of buyers in each period follows a binomial distribution, $AF(i,t)$ can be calculated as: $AF(i,t) = \sum_{j=0}^{N(i,t)} \left\{ \binom{N(i,t)}{j} [p(t)]^{j} [1 - p(t)]^{N(i,t)-j} \left| \frac{j}{N(i,t)} - p(t) \right| \right\}$, which can be further simplified in order to carry out the calculations.

[44] To build the herding statistic we identify a purchase (sale) as an increase (decrease) in the number of units of a given asset held by a PFA. This process is not completely straightforward because we are dealing with portfolios that contain assets with given maturities, such as bonds, for which we unfortunately have no information available. To deal with this issue we assume that an asset reaches maturity if it completely disappears from the portfolios of all PFAs (and does not appear again afterwards) and we do not consider these changes in positions as sales. Of course it is also possible that the asset disappeared because all PFAs simultaneously decided to completely dump the asset. We believe this is unlikely but also checked our results under the opposite assumption that all these cases are sales (not reported) and the broad patterns described below remain.

standard error, using an asset-class-specific probability of buying an asset.[45] Column (1) presents the results obtained computing the statistic across all the available observations. Columns (2) and (3) report the herding statistics computed over those assets traded by more than one PFA and more than half the number of PFAs in operation at a given moment in time, respectively. This is important because the standard herding statistics reported in column (1) may be misleading in the case of Chilean pension funds. As documented in Table 5, most of the assets active in a period are traded by only one PFA, which means that single trades may dominate the standard herding statistics. Column (4) reports the average asset-specific probabilities of buying an asset for each asset class ($p(t)$). For example, the average probability of buying instruments from domestic financial institutions is 74 percent and the average probability of buying mortgage bonds is 25 percent.

The results show that there is robust evidence of herding for domestic corporate bonds, quotas of domestic investment and mutual funds, domestic equities, quotas of foreign investment and mutual funds, instruments from domestic financial institutions, and mortgage bonds, where we see positive and statistically significant coefficients regardless of the number of PFAs trading a given asset. Government and foreign bonds exhibit herding only when considering those instruments traded by an important number of PFAs.[46] In general, the different columns show that the prevalence of herding increases importantly as the number of PFAs trading an asset increases from column (1) to (3); when focusing on column (3) on those assets traded by more than half of the active PFAs we find significant evidence of herding for all asset classes. The economic magnitude of the herding statistic is close to the evidence reported for mutual funds in developed countries in the literature, but still significantly higher in some asset classes when considering instruments traded by most PFAs (column 3). As an example, herding in foreign fixed-income instruments is 15.6 percent when considering assets traded by more than half of PFAs in operation, up from three percent when considering assets

[45] Herding results using probabilities of buying an asset calculated over all asset classes are reported in Appendix 2.
[46] These results indicate that part of the evidence of herding obtained with the standard statistic, reported in Appendix 1, is due to underestimating the probability of trading for some asset classes.

traded by more than one PFA, and up from -0.014 percent (no herding) when considering all assets.

Overall, the results indicate that the presence of herding among Chilean PFAs in many asset classes is particularly prevalent when the asset is being traded by more than one PFA. In other words, although PFAs tend to trade alone and in few assets, when various PFAs are active they historically tend to be on the same side of the trade.

As mentioned above, there is also a dynamic dimension of herding behavior that is related to whether funds follow the herd with a lag, and therefore assets that are more heavily traded in a given period are also more likely to be traded in subsequent moments. This dimension of herding was studied by Sias (2004), who tests the hypothesis that the intensity of trading is serially correlated by estimating the parameters β_t in the following equation for each time period t:

$$\Delta_{i,t} = \beta_t \Delta_{i,t-1} + \varepsilon_{i,t}, , \qquad (2)$$

where $\Delta_{i,t} = \dfrac{Raw_{i,t} - \overline{Raw_t}}{\sigma(Raw)_t}$, $Raw_{i,t}$ is the fraction of PFAs buying asset i at time t among those active ($B(i,t)/N(i,t)$ in the previous notation), and $\overline{Raw_t}$ and $\sigma(Raw)_t$ are the average and standard deviation of $Raw_{i,t}$ among all assets i, respectively. The parameter β_t corresponds, therefore, to the serial correlation of the standardized fractions of PFAs that are buying an asset, which is permitted to vary with time.[47]

Table 7 reports our main results on dynamic herding. Each entry in the table reports the average β_t across time periods for various asset classes, its standard error, and

[47] The reason Sias (2004) standardizes the statistics is that it conducts inference on β_t based on the time-variation of the parameters only (a-la Fama-MacBeth, 1973) and the standardization of the variables controls for changes in their mean and variance over time. Sias' approach is simple and intuitive but cannot be directly applied to the Chilean data Because Chilean PFAs trade infrequently and a large fraction of the assets that are active in a month are not traded in the following one. This means that the sample over which the regressions in equation (2) can be estimated (i.e. the sample of assets traded in two consecutive periods) is different from the sample of traded assets in each period. Moreover, the mean and variance of the standardized statistics are different from zero and one, respectively, in the regression sample. Since the regression sample changes over time, the correct standardization in our case is time varying. We achieve this time-varying standardization by simply estimating the regressions of the raw fractions ($Raw_{i,t}$) including a constant (to remove the mean of the dependent and independent variable) and then correcting the estimated coefficients, multiplying them by the ratio of the standard deviation of the dependent to the independent variable in each regression sample.

the fraction of periods in which the coefficient is significantly greater or lower than zero at the ten-percent level. When considering all the active assets across classes (first row in column 1), we find evidence of significant *negative* serial correlation in trades. Assets that are more intensively bought in a given month are significantly *less* likely to be bought during the next month. Moreover, this significant negative coefficient is obtained in all one-month regressions. The rest of the results reported in column (1) indicate that the negative serial correlation is present in almost all asset classes, with domestic equities being the only asset class in which there is significant evidence of positive dynamic herding. One possible explanation for this finding is that pension funds cannot quickly adjust their positions in domestic equity markets because of the low trading activity of the stocks and, therefore, opt for a gradual change in positions towards their desired levels. In fact, equities are the domestic assets held by pension funds with the lowest annual turnover (trading over market capitalization) of around 15 percent, compared, for instance, with corporate and government bonds, with an annual turnover in 2004 of more than 100 and 400 percent, respectively.[48] Disentangling the extent to which pure herding drives the positive dynamic correlation in domestic equities trading by pension funds would require information on the overall trading activity of individual stocks, which is left for future research.

As in the case of contemporaneous herding, the results for dynamic herding may be driven by the prevalence of single trades. The statistics reported in columns (2) and (3) control for this concern by focusing only on assets that are traded by more than one PFA and more than half the number of PFAs in operation, respectively. The results indicate that indeed an important part of the negative serial correlation comes from single trades, which indicates that assets that are bought by only one PFA in a given month and are traded in the next month, are more likely to be sold (and vice-versa).

At the asset-class level, quotas of foreign investment and mutual funds show significant positive dynamic herding. Under the relatively safe assumption that these quotas are liquid assets, this finding could not be attributed to liquidity considerations unless changing positions in quotas of foreign investment and mutual funds required the gradual liquidation of other illiquid assets. This is unlikely for two reasons. First, unless

[48] World Development Indicators (WDI) database, and Braun and Briones (2006).

those illiquid assets were only sold to buy quotas of foreign investment and mutual funds, this argument would apply to all asset classes and we have shown that there is no evidence of dynamic herding in other liquid assets such as government bonds. Second, PFAs keep large amounts of liquid assets in their portfolio, such as bank deposits, that could be used for quickly adjusting positions. Therefore, this finding should be considered as a strong indication of the presence of herding behavior in this asset class, as well as suggestive evidence that at least part of the positive serial correlation in domestic equities could be the result of this type of behavior.

5.2. Do Pension Funds Trade Frequently?

As mentioned above, the evidence presented in Table 5 regarding the frequency with which a given asset is traded by any of the existing PFAs suggests that PFAs trade infrequently. A typical asset is traded by any PFA once every ten months, and the more actively traded domestic equity and quotas of foreign investment and mutual funds are traded once every two months.

This section shows evidence that complements the previous findings. Summary statistics of PFAs' trading activity reported in Table 8 confirm that they trade infrequently. The table presents three simple statistics: the fraction of all the assets held in a PFA's overall portfolio that the PFA typically trades in a given period (column 1), the share of the portfolio value represented by those assets (column 2), and the actual fraction of the value of the aggregate portfolio that experiences some activity in a given period (i.e., the change in units valued at the initial prices) (column 3).[49] On average, a PFA trades only 11 percent of its assets (which in terms of value account for 22 percent of its portfolio) and the monthly changes in positions in those assets correspond to just four percent of the initial total value of the PFA's assets.

Going beyond these simple statistics of turnover, several measures have been introduced in the literature to study the turnover of a fund, as discussed in Appendix 3. To take into account the specificities of our data, we compute $T_{k,l,t}$, the turnover of fund *k* of PFA *l* at time *t* as

[49] Infrequent trading does not necessarily mean that PFAs do not actively change the relative composition of their portfolios because, even if most assets are not traded, their relative importance depends on the changes experienced by those that are active.

$$T_{k,l,t} = \frac{1}{2}\sum_{i=1}^{i=N_t}\left|w_{i,k,l,t} - w^*_{i,k,l,t}\right|, \quad (3)$$

where $w_{i,k,t,l}$ is the weight of asset *i* at time *t* in the portfolio of fund *k* of PFA *l*, and $w^*_{i,k,t,l}$ is the weight that should be observed for that asset under a benchmark passive strategy. N_t is the number of assets available at time *t*. The average of this turnover measure across time corresponds to the standard turnover statistic for this fund. Different measures are associated with different definitions of the benchmark weight w^* (and therefore of the passive strategy). The Grinblatt et al. (1995) measure considers a constant weight strategy as the passive benchmark while the Ferson and Khang (2002) measure allows for changes in weights due to differences in relative returns across assets.[50]

To account for the variation in turnover across PFAs, fund types, and time periods, we perform inferences based on the following decomposition:

$$\begin{aligned} T_{k,l,t} &= \theta + \theta_k + \theta_l + \theta_t + \varepsilon_{k,l,t}, \\ \varepsilon_{k,l,t} &= \varepsilon_{l,t} + v_{k,l,t}, \end{aligned} \quad (4)$$

where the θ_k, θ_l, and θ_t factors capture fund-type, PFA, and time fixed effects, respectively, which we restrict to add to zero within each dimension, θ is the overall mean, and we incorporate the correlation within PFA-time in the form of the error term.

The overall mean θ and the fund-type factors are reported in Table 9 for both definitions of passive strategy. Since the overall means are positive by construction, the test that they are different from zero is economically meaningless. However, the table also shows that the two statistics are very similar, which means that differences in relative returns do not contribute much to turnover. In terms of size, the measures show that pension funds typically turn over about ten percent of their portfolio in a month. The results also show important differences in turnover across fund types with different risk profiles. In particular, Funds B and C, which have a moderate risk profile, have

[50] Grinblatt et al. (1995) assume $w_t^* = w_{t-1}$, whereas Ferson and Khang (2002) assume $w^*_{i,t} = w_{i,t-1}\frac{1+r_{i,t}}{1+r_{p,t}}$, where $r_{i,t}$ is the holding period rate of return of asset *i* from time *t*-1 to *t* and $r_{p,t} = \sum_{i=1}^{i=N_{t-1}} w_{i,t-1} r_t$ is the return of the portfolio.

significantly less turnover than the average fund. The riskiest fund (Fund A) and the most conservative fund (Fund E) present significantly more turnover than Funds B and C, regardless of the definition of passive strategy considered, with Fund A exhibiting the highest degree of turnover. This is consistent with the hypothesis that Fund A is more actively managed than other types of funds.

The decomposition described in equation (4) can also be trivially extended to test for differences in turnover across asset classes. The estimated factors for the 12 asset classes under analysis, reported in Table 10 under both benchmarks, show significant differences in turnover. Columns (1) and (2), which compare the turnover of various asset classes using the weights of securities in the overall portfolio, indicate that the classes with above-average turnover include assets from domestic financial institutions, domestic government bonds, domestic equity, and quotas of foreign investment and mutual funds. Those with below-average turnover are former pension system bonds, domestic corporate bonds, quotas of domestic investment and mutual funds, foreign bonds, foreign equities, and mortgage bonds. The highest degrees of turnover are observed for domestic government bonds and quotas of foreign investment and mutual funds, respectively, both about two percentage points above the average and both being the asset classes held by PFAs that can be more easily liquidated (except for bank deposits that are not traded in secondary markets) because of the high market turnover of government bonds (400 percent annual turnover) and the liquidity of international secondary markets. The higher-than-average degree of turnover of domestic equity, however, is due to changes in the share of the overall value of funds represented by the asset class as a whole rather than to a high degree of turnover within equities. This can be seen in columns (3) and (4) that measure turnover using the weights of securities within each asset class and where domestic equities exhibits significantly less turnover than average.

The turnover measures described above are useful to determine the extent to which PFAs rebalance their portfolios, but they do not appropriately capture the extent to which that rebalancing is passive or active. In other words, part of the turnover might just be the consequence of passive trading due to: (i) the constant net inflows PFAs receive from current contributors that have not yet retired, or (ii) outflow due to pensioners retiring and leaving the system. Passive trading might also occur because some assets mature and, to reinvest them, PFAs new to purchase new instruments. Therefore, the amount of active turnover and the number of managers willing to change positions over time to maximize returns is lower than the turnover measures reported above.

Another way to gauge the extent to which managers are actively trading their portfolios is to focus on fixed-income instruments (which are also of fixed term). The useful feature of these assets is that they do not need to be traded to recover the initial investment, as managers can wait until maturity. Table 11 presents two statistics per asset class: (i) the average proportion of units of a given security that a PFA incorporates to its portfolio in its first purchase, and (ii) the proportion of units of that security that a PFA liquidates at the security's maturity date; both measures are relative to the maximum number of units of that security that the PFA holds in its portfolio at any time. The figures are rather striking. On average, PFAs purchase most of their fixed-income assets at once (perhaps when those securities are issued) and liquidate almost all of them only upon maturity, not before maturity.[51] That is, although pension funds might hold a large fraction of the outstanding securities, they do not trade them in secondary markets. This runs contrary to the idea that pension funds would provide liquidity to secondary markets.[52]

5.3. Do Pension Funds Follow Momentum Strategies?

Characterizing the investment behavior of Chilean PFAs requires understanding why they change their positions in different assets. The evidence from Section 5.1 indicates that other funds' actions are part of the explanation; PFAs are more likely to buy (sell) assets that are bought (sold) by other PFAs.

In this section we focus on the characteristics of the assets themselves, and test whether trading patterns and changes in portfolio allocations are related to past asset returns; that is, whether Chilean PFAs follow momentum strategies. Momentum trading is a popular investment strategy, and its presence among US investment funds has been widely documented in the literature and been the subject of interest because, together

[51] We do not currently have data on the issue date of most fixed-term securities but we will gather it as part of future research.

[52] Future research will compute these statistics by type of security (short- and long-term, corporate and sovereign). It will also compute hazard rates.

with herding trading, they are considered to be potential causes for increased price volatility in stock markets.

A fund is typically called a *momentum trader* if, on average, it sells assets with low past performance, and purchases securities with high past returns. In short, "buying past winners and selling past losers."[53] On the other hand, a fund that sells past winners and buys past losers is called a *contrarian trader***,** and a fund that follows none of these strategies is a *no-momentum trader*. Of course, momentum and herding strategies are related because momentum trading can look like herding behavior; if all funds follow a momentum strategy they will tend to be on the same side of the trades.

There are different ways of testing for the presence of momentum trading. The simplest one is probably directly testing whether assets with higher past returns are more likely to be bought or sold, which was introduced by Sias (2004) and is related to the regressions used to test for dynamic herding. This can be done by estimating the parameters of the following regression:

$$\begin{gathered} Raw_{i,t} = \alpha + \beta R_{i,t-k} + \theta_t + \varepsilon_{i,t}, \\ \varepsilon_{i,t} = \upsilon_t + \mu_{i,t}, \end{gathered} \tag{5}$$

where $Raw_{i,t}$ is defined as above, $R_{i,t-k}$ is the holding period return between *t-k* and *t* of asset i, θ_t is a time fixed effect, and $\varepsilon_{i,t}$ is an error term that has a time component, so that the estimation of the parameters α and β clusters the errors at the time level and the inference is akin to that obtained from the average of the period-by-period coefficients. The parameter β that measures the sensitivity of the fraction of an asset purchased to its *k*-periods lagged return is the coefficient of interest.

Table 12 reports the estimated β coefficients for the different asset classes, for *k* equaling zero and one, that is, with respect to contemporaneous and lagged returns. The results in column (1) show that the fraction of PFAs buying an asset is significantly positively correlated to its lagged return at a five percent significance level for government bonds, domestic equity, former pension system bonds, and quotas of foreign investment and mutual funds, and negatively correlated for mortgage bonds. The magnitudes of the coefficients are also economically meaningful; for example, a ten

[53] Grinblatt et al. (1995).

percent increase in the return of domestic equity would increase the fraction of PFAs buying that asset in almost three percentage points. The results change in some asset classes when looking at the correlation with contemporaneous returns; the coefficient for domestic equities is negative and significant only at a ten–percent level, foreign equities exhibit contrarian trading, and the coefficient for mortgage bonds changes sign.[54]

Columns (3) and (4) of Table 12 present the same results only considering the assets traded by more than one PFA. The results are similar to those of columns (1) and (2); there is evidence of momentum trading based on lagged returns for domestic government bonds, domestic equity, former pension system bonds, and quotas of foreign investment and mutual funds. However, in this case there is evidence of significant contemporaneous contrarian trading in domestic equities. This suggests that there is no reverse causality (pension funds pushing equity prices up when buying), although it might be due to negative serial correlation of equity returns, which would imply some degree of predictability in the Chilean stock market.

In summary, the results indicate that the fraction of PFAs buying a given government bond, domestic equity, former pension system bond, and quota of foreign investment and mutual fund is significantly larger for those assets that had a relatively larger return during the previous month. This evidence is consistent with the presence of momentum strategies in those asset classes.

It is also possible to look for the presence of momentum strategies by characterizing the trading behavior of each individual fund across assets. This is what the standard measures of momentum based on changes in portfolio weights do. These measures can be described generically as

[54] Deciding on the appropriate lag structure to test for momentum trading is difficult. On the one hand, considering one-month lagged returns loses the within-month reaction of trading to price changes. If momentum strategies are pursued on a daily frequency this may be an important issue that can only be addressed with higher frequency data. On the other hand, the correlation of trading with contemporaneous returns may result from reverse causality since it might be expected that the returns of assets purchased by PFAs would tend to go up. Nevertheless, although this might be the case for domestic assets where PFAs are important players, it is hard to attribute the evidence of momentum trading based on contemporaneous returns to reverse causality for asset classes where PFAs are marginal investors such as quotas of foreign investment funds. Overall, the two correlations offer complementary evidence, although the coefficient with lagged returns is more robust to the reverse causality criticism and is probably a lower bound on the degree of momentum trading for the reasons explained above.

$$LM(k) = \frac{1}{T}\sum_t \sum_{i=1}^{N_t} (w_{i,t} - w_{i,t}^*) R_{i,t-k} \ , \tag{6}$$

with $R_{i,t-k}$ being the rate of return of asset i from period $t-k-1$ to $t-k$, and $w_{i,t}^*$ the benchmark portfolio weight. The statistic $LM(k)$ is called the "lag-k momentum." Different measures arise from different benchmark portfolio weights, lags are allowed for returns to influence changes in the portfolio holdings, and ways of measuring performance. A momentum (contrarian) trader is a fund for which the hypothesis that $LM(k) > 0 \ \ (< 0)$ cannot be rejected.[55] The two standard definitions of the passive benchmark in the literature are those described for the turnover measures. Grinblatt et al. (1995) use the lagged weight $w_t^* = w_{t-1}$ and Ferson and Kahn (2002) use the lagged weight adjusted by relative returns $w_t^* = w_{t-1}(1 + R_{i,t}) / (1 + R_{p,t})$.

A final measure that combines elements of the Sias (2004) approach and the standard measures described above is the momentum statistic of Kaminsky et al. (2004), which instead of portfolio weights uses the percentage change in the units of an asset that a PFA keeps in its portfolio. This measure is defined as

$$M_{i,j,t}(k) = \left(\frac{Q_{i,j,t} - Q_{i,j,t-1}}{\overline{Q}_{i,j,t}} \right) R_{i,t-k} \ , \tag{7}$$

with $Q_{i,j,t}$ being the units held of asset *i* by fund *j* at time *t*, $\overline{Q}_{i,j,t} = \left(Q_{i,j,t} + Q_{i,j,t-1}\right) \big/ 2$ and *k* the lag specification.[56] For a discussion of alternative momentum measures that address some of the problems arising from applying these measures to the Chilean pension fund

[55] To make statistical inference on the significance of the momentum statistic, we consider the associated sequence of random variables $\mathrm{LM}_t(k) = \sum_{i=1}^{N_t} (w_{i,t} - w_{i,t}^*) r_{i,t-k}$. This way, we find that $Lm(k) = \frac{1}{T}\sum_t \mathrm{LM}_t(k)$ and the statistical test for no momentum, expressed as $H_0 : \mathrm{LM}(k) = 0$ could be made by standard procedures.

[56] Assuming that changes in units are uncorrelated across assets within a fund, Kaminsky et al. (2004) directly use this statistic to test for the presence of momentum intensity at the level of individual assets. Although this assumption is plausible, in contrast with the changes in shares that are correlated by construction, we will aggregate the statistic across assets and perform inference across time to ease comparison with the tests offered by the two other measures described above. By doing so, we can be certain that differences in the results of the tests across measures are only due to the special characteristics of each of them and not to assumptions regarding the degrees of freedom available for inference. If individual assets were considered *iid*, then everything would become significant.

data, such as the entry and exit of PFAs and the importance of passive portfolio changes, see Appendix 4. Despite further corrections, the results there are broadly consistent with the results reported here.

Our main results for the presence of momentum and contrarian trading based on the measures described above are reported in Table 13. Each entry in the table reports the average momentum statistic across PFAs, its standard error, the level of significance of the one-tailed test that each average is greater or lower than zero, depending on its sign, and the fraction of PFAs for which the null hypothesis of momentum and contrarian trading cannot be rejected at the ten-percent level. When testing whether a specific fund is a momentum trader the inference is performed across time, but when testing for the overall presence of momentum strategies the inference is conducted across funds only. Columns (1) to (3) show the three statistics based on lagged (previous month's) returns.

For the overall group of assets no statistic can reject the null hypothesis that there is momentum trading across PFAs, and at the individual fund level the hypothesis cannot be rejected for a fraction of funds that vary between 38 and 54 percent. As usual, there is important variation across asset classes. Only domestic equities and quotas of foreign investment and mutual funds display robust evidence of momentum trading regardless of the specific measure used, while for government bonds, foreign fixed-income, and foreign equities the hypothesis cannot be rejected in two of the three measures. The evidence is mixed for the other asset classes.

Asset classes for which the hypothesis of momentum trading cannot be rejected are also typically those with the highest fraction of individual PFAs for which this hypothesis cannot be rejected. For instance, the hypothesis of momentum trading in domestic equities cannot be rejected for 30 percent of the PFAs in operation during the period of our analysis. In the case of quotas of foreign investment and mutual funds this fraction is 50 percent.

Interestingly, there is little robust evidence of contrarian trading across asset classes. In some classes, such as mortgage bonds, the hypothesis of contrarian trading cannot be rejected for two of the measures but the third measure indicates momentum trading. The best evidence for the presence of contrarian trading comes from quotas of domestic investment and mutual funds, for which the hypothesis cannot be rejected according to the Ferson and Khang (2002) and Kaminsky et al. (2004) measures, but even in this case the hypothesis of contrarian trading cannot be rejected for only four percent of the PFAs. Among the measures, the Grinblatt et al. (1995) measure is the one that results in more rejections of the hypotheses of no-momentum or contrarian trading, followed by the Kaminsky et al. (2004) and the Ferson and Khang (2002), respectively.

Columns (4) to (6) present the momentum statistics based on contemporaneous returns. There are two aspects of these results that are worth highlighting. First, the hypothesis of momentum trading in domestic equity cannot be rejected only for the Grinblatt et al. (1995) measure, while the other two measures do not allow us to reject the hypothesis of contrarian trading, which is consistent with the results from the regression approach reported in Table 12. Second, there is evidence of significant contemporaneous momentum trading for mortgage bonds and government bonds, which could be driven by reverse causality because of the importance of PFAs in the market for these assets.[57] However, as in the regressions presented in Table 12, there is also evidence of contemporaneous momentum trading for quotas of foreign investment and mutual funds, which is unlikely to be driven by endogeneity and suggests that at least part of the contemporaneous evidence of momentum trading in other asset classes is indeed related to momentum trading within the current month.

Although in principle the momentum strategies followed by PFAs have the potential of destabilizing capital markets and increasing price volatility, this does not seem to be happening in Chilean capital markets in general, as can be seen in Table 14 that shows the results of regressing an asset’s return on the lagged fraction of PFAs buying that asset for all domestic assets traded in secondary markets. The only asset class in which past trading affects future prices is government bonds, which is somewhat surprising considering the tradability of these assets (as measured by their overall market turnover ratio) but not considering the importance of PFAs in this market.

5.4. Does Momemtum Explain Herding?

As mentioned above, momentum strategies are one form of herding behavior. If all funds buy assets with high past returns they will all tend to be on the same side of the

[57] Around 100 and 60 percent of the amount outstanding in each of these asset classes are in the hands of PFAs, respectively, according to the Asociación Gremial de Administradoras de Fondos de Pensiones (2007).

market. One indication that this is plausible is that the asset classes for which there is robust evidence of herding (i.e., domestic equities and quotas of foreign investment and mutual funds) also exhibit robust evidence of momentum trading. To test whether momentum strategies can account for the evidence on herding described above we run a series of regressions to measure herding controlling for the influence of past returns. In the case of contemporaneous herding, we estimate:

$$H_{i,j,t} = \alpha + \gamma R_{i,j,t-k} + \varepsilon_{i,k,t}, \tag{8}$$

where $H_{i,k,t}$ is the herding statistic of asset i in class j at time t and $R_{i,j,t-k}$ its return in $t-k$. The tests reported in Section 5.1 were basically tests of the hypothesis that $\alpha = 0$. These regressions test whether $\alpha = 0$ controlling for the returns of the assets. If herding is unrelated to the returns then the hypothesis should again be rejected. In the case of dynamic herding we proceed similarly by estimating

$$Raw_{i,j,t} = \alpha + \beta Raw_{i,j,t-1} + \gamma R_{i,j,t-k} + \theta_t + \varepsilon_{i,j,t}, \tag{9}$$

where the β coefficient captures the mean of β_t coefficients reported above. If the dynamic herding documented for some asset classes is exclusively driven by momentum strategies, β should not be statistically significant after controlling for $R_{i,j,t-k}$.

The results of contemporaneous herding regressions are summarized in Table 15. They show that this type of herding cannot be explained by momentum trading. The estimated value of α in asset classes where there was evidence of herding is always positive and statistically significant after controlling either by the contemporaneous or lagged return. The tendency of Chilean PFAs to be on the same side of trades seems to be driven by a desire to follow others instead of focusing on assets with specific patterns of returns.

The results of the dynamic herding regressions are reported in Table 16. The first column of the table reports the estimated β coefficient when lagged returns are not included in the specification and shows that domestic equity and quotas of foreign investment and mutual funds exhibit dynamic herding, as was shown in Table 6. The β coefficients after controlling for lagged returns are presented in column (2). Although there is still significant evidence of dynamic herding for domestic equities, the evidence for quotas of foreign investment and mutual funds disappears. This indicates that the dynamic herding in the latter asset class was mostly driven by the use of momentum strategies.

5.5. Regulations, Crises, and Trading Patterns

During our sample period there have been various events that could affect the degree of herding, turnover, and momentum, including two global financial crises and several important regulatory reforms. We next analyze the impact of those events on the three types of measures.

The time variation of the contemporaneous and dynamic *herding measures* can be used to determine the impact of crisis times and changes in regulation. The evolution of the contemporaneous and dynamic herding statistics for the asset classes that exhibit robust herding are depicted in Figures 15 to 17, along with the dates of various regulatory events and the Asian and Russian financial crises.

Global financial crises are times of turmoil that can lead investors to disregard their individual information and follow the herd, but also times in which it is harder to observe and forecast what others are doing. Figures 15 to 16 show that the Asian financial crisis did not affect importantly the degree of contemporaneous herding in most asset classes. This is not surprising because Chile did not experience major problems immediately after the onset of this event, but only after the beginning of the Russian financial crisis of 1998. In fact, the figures show that this latter event disrupted the pattern of herding resulting in a decline in the herding statistic in those asset classes that show robust evidence of herding over the whole period. As shown in Figure 17 dynamic herding was also reduced by the Russian crisis; after the crisis it was less likely to buy the same asset in two consecutive periods. These results remain unchanged for contemporaneous and dynamic herding when considering assets traded by more than one PFA.

The most important regulatory reforms of the pension system during the 1996-2005 period were the introduction of multiple funds, which happened in two stages in

2000 and 2002, and the increase of the minimum return band in 1999.[58] The exact dates of these events are also depicted in Figures 15 to 17. It is difficult to disentangle the individual impact of the widening of the band of returns because it occurred only a year after the onset of the Russian crisis, but the figures show that there is no appreciable decrease in herding. If anything, the degree of contemporaneous herding seems to increase for various asset classes such as domestic equity and government bonds even with respect to the pre-Russian-crisis level. This finding does not support the claim that herding was mainly due to the tightness of the band because that should have resulted in a notorious decline in the degree of herding around these dates. The most evident change is observed after the introduction of the multi-fund system in 2002, when both contemporaneous and dynamic herding decreased importantly for various asset classes and in the case of domestic equity they were no longer statistically significant on average.

To study the time variation in *turnover,* Figure 18 plots the time fixed effects of the Grinblatt et al. (1995) measure estimated in equation (4) for the entire 1996-2005 period. The months in which turnover is significantly higher than average are marked with a cross. The figure is dominated by the high turnover observed after the introduction of the multi-fund system. Clearly, this regulatory change led PFAs to make important adjustments in their different fund types to take advantage of the broader set of investment opportunities offered by the relaxation of the investment restrictions associated with the riskier portfolios. However, there are some other interesting episodes that are obscured by this event. For instance, turnover is also significantly above average following the Russian crisis. This can be seen in Figure 19, which shows the evolution of turnover before the multi-fund period. If we replace the time fixed effects for a Russian crisis dummy that takes on the value one after August 1998, we find that turnover was six percent larger than average after the crisis (and 12 percent higher than before the crisis). This indicates that Chilean PFAs significantly re-balanced their portfolios during this period.[59]

[58] The law that widened the band for the calculation of the returns is the same that introduced the first multi-fund, but the actual portfolios were not implemented until the following year.
[59] This is not mechanically due to changes in asset prices since results for the Ferson and Kahn (2002) measure, which controls for this possibility, are essentially similar (although not reported here).

One may be concerned that some of the observed time variation in turnover could be due to the entry and exit of PFAs. If a PFA that is about to disappear trades very actively, it could be possible to confuse periods of exit with periods of high turnover. Of course, this entry and exit could also affect the average level of turnover. This is not the case. We re-estimated the factors and their significance levels after dropping all observations of a PFA six months before merging or exit and obtained almost identical results (not reported). The correlation between the time fixed effects estimated with all data and dropping exit periods is 0.98.

Crises and regulatory events can also affect the extent to which PFAs follow *momentum strategies*. Testing for this possibility requires focusing on the time variation of the momentum statistics, which is done by estimating time fixed effects in a similar fashion as in the decomposition of the turnover measures (see Appendix 4). The time path of those fixed effects for the Grinblatt et al. (1995) and Kaminsky et al. (2004) measures is shown in Figures 20 to 21. There are two events that roughly coincide with local increases in momentum: the widening of the minimum return band in late 1999 and the Russian crisis.[60] Tests for the significance of these events that rely on local variation have very low power and can only reject the null of no change in the degree of momentum trading for the increase of the regulatory band when comparing the degree of momentum trading in 1999 and 2000 to the earlier years. However, since the widening of the band closely coincided with the introduction of Fund D in early 2000 it is impossible to separate each event. On the other hand, the introduction of the multi-fund system is associated with a persistent decline in momentum that is statistically significant.[61]

Another way of determining the impact of regulation on investment behavior is comparing the conduct of fund types that face different regulatory constraints. One of such differences is in the minimum return band, which has different values across fund types with different risk profiles. Although the band is typically larger for riskier funds, there is no reason to expect that band to be equally binding after controlling for the

[60] It is unclear a priori the impact that the widening of the regulatory band should have on the prevalence of momentum strategies; depending on whether these strategies are the norm in the industry. If the regulatory band leads PFAs to follow conventions, the widening of the band should increase the incentives to pursue individual strategies and depart from the norm. If momentum strategies are the norm, they should be less prevalent, and the contrary if they are not.

[61] This decline does not eliminate momentum trading during the multi-fund period.

different risk profiles of each fund. For instance, the band for the riskier fund A is twice as wide as the band for the most conservative fund E, although fund A is not necessarily twice as risky as fund E. Most importantly, groups of funds with different risk profiles face the same regulatory band, for instance, funds C, D, and E face a band of two percentage points around the average return despite their different risk profiles.

To test for the presence of differences in herding strategies across fund types, we treat each of them as a separate portfolio (i.e., each PFA has five different portfolios) and compute the herding statistics for every asset class and combination of PFA and fund type. Then, we build a nested test of the hypothesis that the average herding statistic of a given fund type is equal to the overall mean across all fund types for each asset class separately. The results of this test, reported in Table 17, show that the herding statistics in Fund C are indeed significantly different from the mean across fund types considering all assets and this is also the case for most individual asset classes. Since Fund C presents the riskiest profile among the three funds facing a two percent minimum return band (Funds C, D, and E), it might have the most binding regulatory band among these three funds. If this were indeed the case, the finding that herding is stronger and more prevalent in Fund C would be indirect evidence that at least part of the herding behavior is motivated by regulatory constraints. However, under this hypothesis we would expect to observe a similar difference between Funds A and B, which are subject to the same regulatory band and have different risk profiles. Concretely, we would expect to see the riskier Fund A exhibiting more herding than Fund B. However, this is not the case. In fact, the point estimates of the herding statistic are typically higher for Fund B and in most cases neither Fund A nor Fund B exhibit herding measures significantly different from the overall average.

In sum, the comparison of herding statistics across fund types does not provide robust evidence that the herding behavior of Chilean PFAs is the result of regulatory restrictions such as the minimum return band. This would suggest that the characteristics of the industry or of the asset markets are the most likely forces behind this behavior. Differences in the degree of regulatory constraints faced by different fund types can also be exploited to test for the impact of these regulations in the prevalence of momentum strategies across fund types. To this end, we treat each combination of PFA and type of fund as a portfolio (i.e., each PFA has five different portfolios), compute the momentum statistics for each PFA-fund-type at each point in time, and decompose the variation of these measures in PFA, asset-class, and time fixed effects as explained in Appendix 4, restricting the various sets of fixed effects to have zero mean and represent, therefore, deviations from the overall mean of the measure. The results of this decomposition are reported in Table 18.

The results show little differences in momentum among fund types. Only Fund A exhibits significantly lower momentum compared to the other fund types for most statistics. Since Fund A faces the wider return bands and the lightest set of quantitative restrictions, we cannot separate which of these regulatory elements might be behind the smaller prevalence of momentum strategies in this case.

6. Conclusions

This paper has provided a first step at analyzing in a systematic way the investment patterns of Chilean pension funds. The paper documents a large amount of new stylized facts and results. Notably, pension funds hold a large proportion of their portfolios in assets that can be easily liquidated, namely, bank deposits, government bonds, and more generally short-term instruments among fixed-term securities. Moreover, pension funds do indeed tend to hold similar portfolios at the asset-class level and herd in their investment decisions. Furthermore, they trade relatively little, changing their positions very infrequently and holding assets up to maturity. Finally, there is a significant fraction of funds whose trading follows a momentum strategy; they buy past winners and sell past losers (in terms of asset returns).

Although we lack good benchmarks for comparison, overall, the patterns described in the paper do not seem to confirm the initial expectations about the role of pension funds as drivers of overall capital market development. On the bright side, pension funds seem to absorb a large amount of bonds in primary markets, likely allowing the corporate sector to issue that type of securities and effectively contributing to the development of that market. However, the characterization, taken as a whole, is difficult to align with the initial ideas about pension funds as agents that contribute in many different ways to the development of domestic capital markets. For example, it is difficult to reconcile the fact that pension funds hold a large fraction of bank deposits, government paper, and short-term assets with the idea that they help foster long-term financing for corporations. At first sight, these holdings do not seem to respond to the pension fund liquidity needs for retiring pensioners. For example, the amount paid in pensions in December 2005 corresponded only to 0.6 percent of the PFAs' assets.[62] Also, even Fund A, in which pensioners close to retirement cannot invest, has a significant fraction of bank deposits and government paper, and the maturity structure of its fixed-income securities is tilted towards the short term. In the case of the less risky funds, most of the fixed-term assets have a term to maturity of up to three years, and a significant proportion mature within one year. This type of investment is not explained by the lack of investable instruments because pension funds invest only in a fraction of the existing assets. Furthermore, the fact that pension funds tend to display little turnover does not seem to square well with the idea that they contribute to the liquidity of secondary markets. Also, the high degree of herding behavior indicating that all funds invest in the same assets suggests either that (i) all funds arrive independently at the same conclusion over time and therefore purchase and sell exactly the same assets that maximize the pensioners' long-term wealth or, perhaps more likely, (ii) funds follow each other in their investment strategies. Although we cannot reject either explanation, it is difficult to think that the former is driving the results. Moreover, the finding that pension funds follow momentum strategies in their trading activities (with respect to past returns but not current returns) does not bold well with the idea that pension fund managers collect independent and superior information (relative to other market participants) and invest accordingly. If fund managers knew which stocks would do well they would not purchase a security after its price has increased (and right before its price is about to stay flat or fall), they would purchase it in advance. In sum, our findings suggest that at least the initial ideas that motivated the introduction of pension funds as dynamic agents of secondary capital market development would need to be revisited.

Determining the extent to which the patterns documented in this paper are the result of the regulatory environment, managers' incentives, or the liquidity of different

[62] This is the sum of the programmed and temporary retirement outlays paid by the system as a percentage of the system's assets.

assets, should be an important part of future work, but some hypotheses can already be drawn from this work. First, the evidence does not suggest that regulations fully determine the trading patterns of pension funds. The only constraint that has become binding over time is the quantitative restriction on holdings to invest up to 30 percent of their portfolio abroad; but even in this case pension funds did not hit the investment limit for almost two years after the limits were increased from the previous 20 percent limit.[63] The other many restrictions do not appear at first hand to be very constraining. For example, pension funds only invest in a subset of all the investable instruments. Moreover, when regulations were relaxed such that the minimum return band was expanded (giving funds effectively more flexibility to allocate their investments), the amount of herding behavior did not diminish. Second, the fact that pension funds continue to herd after regulations have been relaxed suggests that there is something inherent to the competition among funds that leads them to hold similar portfolios and make similar adjustments over time. That is, the incentives for managers might also play a role in the way that pension funds invest.

The third factor, the liquidity of certain assets, might also be explaining to some degree the patterns described in this paper. This liquidity might be behind the low turnover ratios found. This low turnover might be driven by the limited availability of assets in which pension funds want to invest. Thus, pension funds purchase any security that they like and that becomes available, and hold it. Moreover, the fact that pension funds seem to hold bonds up to maturity might be explained by the liquidity of those instruments. Holding them up to maturity allows funds not to trade those bonds in illiquid secondary markets; furthermore, this feature of bonds might also explain the pension funds' preference for that type of security relative to equity, which will force them to participate in secondary markets. However, one would still need to explain why pension funds hold even government bonds up to maturity, given that they're usually perceived to be liquid instruments. Alternatively, one could argue that government bonds are kept because there are no other liquid and desirable instruments in which to invest. Or perhaps pension funds just prefer not to trade and hold all fixed-term asset to maturity. In any

[63] In March 2004, investment limits on foreign securities and investments abroad through domestic mutual and investment funds were increased to 30 percent of the funds managed by a single administrator. These limits were reached by the end of 2005.

case, we cannot reject that pension funds might be holding bonds because they are preferred relative to the alternatives in terms of risk-adjusted returns. Furthermore, the fact that pension funds follow dynamic herding (especially so when trading domestic equity) is consistent with the hypothesis that funds make trades sequentially (as supposed to all at once) to avoid affecting prices with their trades (which often happens in illiquid markets).

For sure, much more research remains to be done to understand better the patterns uncovered in this paper. A large part of that research could be devoted to obtaining good benchmarks against which pension funds' asset allocation could be evaluated, something that this paper lacks and that would help derive more precise conclusions. In particular, future work could focus on four different but related areas: (i) the investment behavior, (ii) the role of regulations, (iii) the role of incentives, and (iv) the role of liquidity.

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Appendix 1: How Much Do Pension Funds Actually Diversify Internationally?

An interesting issue that deserves further analysis is the actual degree of international diversification of PFAs. As described in the paper, most of PFAs' foreign investment is in quotas of investment and mutual funds incorporated in financial centers such as the US and Luxemburg. This is probably related to regulatory restrictions.

Under current law, PFAs are restricted to invest in foreign assets issued in specific markets (and meeting some risk criteria). In the case of equities, there is a close map between the nationality of the market of issuance and the underlying company, but this is not the case for investment funds, particularly for investment funds focused on foreign debt or equity. For instance, a US investment fund specialized in emerging markets would be considered as an investment in a US asset, although the underlying assets are not really located in the US.

In principle, PFAs can use these types of funds to invest indirectly in markets in which they may not be able to invest in a direct way. Therefore, the true degree of international diversification (and exposure) of Chilean PFAs may well be much larger than apparent from a first look at the origin of the assets directly held in their portfolio. Determining the true degree of diversification is difficult because it requires gathering information on the portfolio composition of the investment funds in which PFAs invest but is certainly important to determine the true exposure of these funds to upheavals in international markets.

Appendix 2: Variation in Herding Measures

This appendix provides alternative estimates of the herding measures. Appendix Table 1 reports results on contemporaneous herding, for which the probability of buying $p(t)$ is computed using information from all assets, as is usually done in the literature (see Lakonishok et al.,1992). This approach assumes that the probability of a PFA buying a security is constant across securities at each point in time. We deviated from this approach in the main text because of the diversity of securities held in PFAs' portfolios, which even include a few assets that are not traded in secondary markets (banks deposits and OTC currency derivatives). But we report the results here for completeness. This table is similar to Table 6. Each entry of the table reports the mean of the herding statistic across a group of assets and its corresponding standard error. Column (1) presents the results obtained computing the statistic across all the available observations, and shows that overall and for each asset class the hypothesis of no herding is always strongly rejected. The results also show some important degree of variation across asset classes with the highest degree of herding in mortgage bonds and quotas of domestic investment and mutual funds (at around seven percent), and the lowest in former pension system bonds and government bonds (at 0.6 and three percent respectively). The magnitude of the statistics, with an average of about five percent, is also large compared to those previously reported in the literature of mutual funds in the US (around two percent).

Columns (2) and (3) show that there are some interesting differences with respect to the results in column (1). First, in most asset classes the degree of herding progressively increases as we restrict the analysis to assets traded by a larger number of PFAs; the overall statistic becomes almost four times larger when looking only at those assets more intensively traded and the increase is even bigger in some asset classes like domestic corporate bonds whose statistic increases six fold. Accordingly, the economic magnitude of herding is in these cases much larger than that previously reported in the literature. Second, the hypothesis of no herding cannot be rejected for former pension system bonds, the non-standard assets that are prevalent in the portfolios of Chilean PFAs. Thus, the evidence of herding reported in column (1) for those instruments is completely driven by single trades.

The standard herding statistics may also be potentially misleading in the Chilean PFA industry because these funds invest in a broad set of assets. The standard methodology outlined above uses information from all assets in PFAs' portfolios to compute the probability of trading $p(t)$. In other words, this probability is assumed common across asset classes. Despite the gains in power offered by this assumption, it may be incorrect when considering fundamentally different asset classes, such as bank deposits and quotas of investment and mutual funds. The differences in the average fraction traded across asset classes reported in Table 5 indicate that trading probabilities may indeed vary importantly across classes, which is reflected in the results reported in Section 5.1.

Appendix 3: Alternative Turnover Measures

Several measures have been introduced in the literature to determine the extent of the changes in portfolio composition that aim to capture the deviations from a "passive" strategy, with different measures varying on their definition of this strategy. These differences have to do with how to deal with heterogeneity in relative returns and flows of funds to (out of) the portfolio resulting from dividends, coupons, and injections (outflows).

The family of turnover measures can be generally described by:

$$Turnover = \frac{1}{2}\frac{1}{T}\sum_{t=1}^{t=T}\sum_{i=1}^{i=N_t}\left|w_{i,t} - w_{i,t}^{*}\right|, \tag{10}$$

where $w_{i,t}$ is the weight of asset *i* at time *t* in the portfolio, and $w_{i,t}^{*}$ is the weight that should be observed for that asset under a benchmark passive strategy. N_t is the quantity of assets available at time *t*. By construction, the turnover measure takes values between zero and one and captures the fraction of the portfolio that is actively or passively reallocated in a given period.

Different measures are associated with different definitions of the benchmark weight w^{*} (and therefore of the passive strategy). We consider two definitions. The first one, proposed by Grinblatt et al. (1995) considers a constant weight strategy as the passive benchmark and, therefore, assumes that $w_t^{*} = w_{t-1}$. The second measure allows for changes in weights due to differences in relative returns across assets, and has been suggested by Ferson and Khang (2002). In this case, the expected weight under a passive strategy corresponds to $w_{i,t}^{*} = w_{i,t-1}\frac{1+r_{i,t}}{1+r_{p,t}}$ where $r_{i,t}$ is the holding period rate of return of asset *i* from time *t*-1 to *t* and $r_{p,t} = \sum_{i=1}^{i=N_{t-1}} w_{i,t-1}r_t$ is the return of the portfolio. Importantly, in contrast to the analysis of herding in which we focus on the PFAs' aggregate portfolio, here we focus exclusively on the individual fund types held by each PFA. This focus is more appropriate because regulatory restrictions to portfolio composition are mostly defined at the fund type level instead of the PFA level, which is not the case for trades.[64]

The turnover statistics are positive by construction so the hypothesis that they are greater than zero is meaningless, but they can be used to test for differences across PFAs, fund types, and time. Proper testing, however, requires some additional considerations. First, although the natural unit of analysis is each specific portfolio held by a PFA, there are some regulatory restrictions that apply to the PFA as a whole and induce correlation in the changes in composition of all of its funds. Thus, we cannot safely treat the funds of a same PFA as independent observations. Second, as discussed above, our sample includes PFAs and fund types that exist in different periods of time because of entry, mergers, exit, and regulatory changes. To the extent that there are periods with intrinsically different levels of turnover we can incorrectly attribute them to differences in turnover across PFAs or funds that exist in different periods.

Appendix 4: Alternative Momentum Measures

The standard momentum statistics described in Section 5.3 have two shortcomings when applied to the Chilean pension fund data. First, they were developed to compare funds that operated over the same period of time. In contrast, the Chilean data include funds that operated in different moments because of entry, exit, and merging activity. The comparison of funds that do not completely overlap is complicated by the presence of important aggregate and regulatory events during the period that affect only those funds in operation at the time of the event. Second, as mentioned in multiple occasions, trading activity in Chilean PFAs is very infrequent and most of the changes in portfolio allocations are passive. This makes the interpretation of the first two measures difficult.

There are several ways of dealing with these potential shortcomings. The differences in the periods of operation of the funds in our sample could be addressed by focusing only on those funds in continuous operation during a sub-sample of the data, but this would lead us to disregard an important amount of data and lose power in all of our

[64] Instead of adjusting the lagged weight by relative returns, it is also possible to use past prices to value the contemporaneous portfolio so that changes in prices do not affect turnover. Results are similar to those produced by the other methods and are available upon request.

tests. Instead, we follow a regression approach to extract the common time components and focus only on the within-period variation of the data. To this end, we compute the monthly value of the momentum statistic for each PFA (before averaging across time) as:

$$LM(k,t) = \sum_{i=1}^{N_t} (w_{i,t} - w^*_{i,t}) R_{i,t-k} \ . \tag{11}$$

In addition, we estimate the parameters of the following regression:

$$\begin{aligned} LM(j,t) &= \theta_j + \theta_t + \varepsilon_{j,t} \ , \\ \varepsilon_{j,t} &= \upsilon_t + \mu_{j,t} \ , \end{aligned} \tag{12}$$

where θ_j and θ_t are PFA and time fixed effects, respectively. Since the errors have a time component, in absence of time fixed effects the PFA fixed effects would correspond to the momentum statistics reported above. Thus, adding the time fixed effects results in estimators of the average momentum statistics after cleaning any differences resulting from timing. The resulting average PFA statistics (corresponding to the average PFA fixed effects) are reported in Appendix Table 2. The results are remarkably similar to those reported above, which indicates that differences in timing are not driving those results.

Addressing the issue of infrequent trading requires using measures that are less sensitive to passive changes in allocation. The Kaminsky et al. (2004) measure has this characteristic, but as discussed above, it equally weights all changes in units of assets regardless of their importance for PFA portfolios. Therefore, one option to deal with this concern is to build a hybrid measure that does not count passive changes in weights but properly weights the changes in units by their weight in the portfolios. This can be easily done by using a version of the Grinblatt et al. (1995) measure based on the change in weights valued at last period's prices. The momentum statistic would therefore be:

$$LM(k) = \frac{1}{T} \sum_t \sum_{i=1}^{N_t} \left(w_{i,t}(p_{t-1}) - w_{i,t-1} \right) R_{i,t-k} \ , \tag{13}$$

where $w_{i,t}(p_{t-1})$ is the weight of asset *i* in the portfolio at time *t* valued at the asset prices of *t*-1. The results of this exercise are reported in Appendix Table 3, which presents the Grinblatt et al. (1995) *L0M* and *L1M* statistics built in this manner. The results at the aggregate level show again evidence of momentum trading based on lagged returns but contrarian trading based on contemporaneous returns (akin to what we obtained with the contemporaneous Ferson and Khang, 2002, measure in Table 13). There is still significant evidence of lagged momentum trading for domestic equities and quotas of foreign investment and mutual funds, which highlights the robustness of the evidence of momentum strategies in these asset classes, and some evidence of lagged momentum trading for foreign fixed-income assets and foreign equities.

To analyze the degree of regulatory constraints faced by different fund types, we treat each combination of PFA and type of fund as a portfolio and compute the momentum statistics for each PFA-fund-type at each point in time. We decompose the variation of these measures in PFA, asset-class, and time fixed effects, restricting the various sets of fixed effects to have zero mean and represent, therefore, deviations from the overall mean of the measure. Because all five portfolios held by a PFA are probably correlated and to conduct proper inference, we decompose the variation of the fund-type statistics as:

$$\begin{gathered} LM_{j,l,t} = \theta + \theta_j + \theta_l + \theta_t + \varepsilon_{j,l,t}\,, \\ \varepsilon_{j,l,t} = \upsilon_{j,l} + \mu_{j,l,t}\,, \end{gathered} \tag{14}$$

where $LM_{j,l,t}$ is the momentum measure for PFA j, portfolio l, at time t. The θ's are fixed effects in the dimension indicated by the sub-index, restricted to have zero mean within their dimension. Therefore, the θ_l parameters represent the deviations of the average momentum statistic in each portfolio type with respect to the overall mean. Table 9 presents results that were estimated similarly as in equation (14) after adding an asset-class fixed effect to the specification. The results without asset-class fixed effects are not presented but are available upon request. The differences across fund types resulting from equation (14) are unconditional and those resulting from Table 9 (adding asset-class fixed effects) are conditional on the asset-class combination of each portfolio type, which is important because of the differences in momentum across asset classes reported above.

Table 1
PFA Holdings by Asset Class and Fund Type

This table presents the average across PFAs and time of the portfolio share of each asset class by fund type. First, we calculated the portfolio weight of each asset class per PFA and fund type, for each month. Then we averaged across PFAs for each fund type and month. Panel A presents the average across time for the entire sample period (July 1996 to December 2005) and Panel B presents the results for December 2005. The dashes indicate the asset classes for which there are no holdings in a certain fund type. For example, Fund E is the most conservative fund type and no investments are allowed in Foreign Equity or in Domestic or Foreign Investment and Mutual Funds.

Panel A. Average PFA Portfolio Share by Asset Class and Fund Type (1996 - 2005)

	Fund Type				
	Fund A	Fund B	Fund C	Fund D	Fund E
Domestic Assets					
Former Pension System Bonds	1.4%	3.1%	4.3%	7.1%	17.1%
Corporate Bonds	1.3%	4.7%	5.6%	8.8%	10.5%
Financial Institutions	12.6%	18.6%	16.5%	21.4%	16.4%
Government Paper	5.0%	13.0%	27.5%	26.9%	41.8%
Investment and Mutual Funds	2.8%	3.5%	3.3%	1.7%	-
Equity	24.3%	18.8%	15.6%	9.1%	3.8%
Mortgage Bonds	2.0%	6.1%	14.3%	10.9%	17.6%
Foreign Assets					
Fixed Income	1.1%	2.0%	2.6%	4.5%	6.8%
Investment and Mutual Funds	47.7%	28.9%	10.2%	8.5%	-
Equity	2.0%	0.7%	0.3%	0.4%	-

Panel A. Average PFA Portfolio Share by Asset Class and Fund Type (December 2005)

	Fund Type				
	Fund A	Fund B	Fund C	Fund D	Fund E
Domestic Assets					
Former Pension System Bonds	0.9%	2.3%	4.0%	7.3%	14.0%
Corporate Bonds	1.8%	4.5%	8.4%	8.9%	15.5%
Financial Institutions	12.9%	20.4%	24.9%	26.8%	16.8%
Government Paper	3.0%	7.7%	13.5%	24.8%	37.4%
Investment and Mutual Funds	1.6%	3.6%	3.5%	2.1%	-
Equity	16.6%	17.7%	14.9%	10.2%	-
Mortgage Bonds	1.2%	3.5%	6.2%	7.4%	12.8%
Foreign Assets					
Fixed Income	0.5%	0.6%	0.8%	0.9%	2.7%
Investment and Mutual Funds	58.5%	37.6%	22.4%	10.1%	-
Equity	-	0.7%	-	-	-

Table 2
PFA Maturity Structure by Fund Type

This table presents the average across PFAs and time of the portfolio share at different terms to maturity by fund type. First, we calculated the portfolio share of each PFA and fund type, per month, at different terms to maturity. Then we averaged across PFAs for each fund type, month, and term to maturity. Panel A presents the average across time for the entire sample period (July 1996 to December 2005) and Panel B presents the results for December 2005. The results present the accumulated portfolio shares for each term to maturity.

Panel A. Average Accumulated PFA Portfolio Share per Fund Type and Maturity (1996 - 2005)

Term to Maturity (in days)	Fund Type				
	Fund A	Fund B	Fund C	Fund D	Fund E
Under 30	12.2%	6.8%	3.5%	4.3%	3.7%
Under 90	25.6%	16.0%	10.3%	10.6%	9.1%
Under 120	29.2%	19.2%	11.9%	12.9%	10.7%
Under 360	60.2%	42.1%	23.9%	30.7%	23.6%
Under 720	69.4%	53.2%	32.4%	44.1%	40.9%
Under 1,080	75.8%	64.9%	44.3%	60.4%	59.0%

Panel B. Average Accumulated PFA Portfolio Share per Fund Type and Maturity (December 2005)

Term to Maturity (in days)	Fund Type				
	Fund A	Fund B	Fund C	Fund D	Fund E
Under 30	7.5%	5.1%	3.6%	3.9%	1.7%
Under 90	18.8%	13.7%	11.3%	9.6%	4.7%
Under 120	27.0%	21.3%	16.7%	15.0%	6.6%
Under 360	59.3%	47.6%	38.8%	33.5%	16.8%
Under 720	69.3%	59.6%	51.7%	49.9%	32.9%
Under 1,080	75.5%	68.6%	61.6%	65.9%	50.4%

Table 3
Average Distance Across Asset Classes

This table presents the average distance across asset classes, for each fund type. First, we calculated the distance of portfolio shares across asset classes for all PFA pairs and then we averaged the value of the distance across all PFA pairs.

	Average Distance Across Asset Classes	
	December 2005	2003-2005
	(1)	(2)
Fund A	7.4%	10.6%
Fund B	7.4%	10.0%
Fund C	9.7%	10.0%
Fund D	16.1%	12.7%
Fund E	15.1%	13.7%

Table 4
Proportion of Approved Instruments Held by PFAs

This table presents the number of instruments approved by the Risk-Rating Commision (CCR) by instrument type, for Domestic Equity and Domestic and Foreign Investment and Mutual Funds, from 2002 to 2005, as of December of each year. Panel A presents the number of instruments approved per year and Panel B presents the average across PFAs of the percentage of assets held in portfolio relative to the number of approved instruments, per year. The dashes indicate that data is unavailable for Domestic Mutual Funds and Foreign Investment Funds for the year 2002.

Panel A. Number of Assets Approved as of December of Each Year

	2002	2003	2004	2005
Domestic Equity	83	92	96	110
Domestic Investment Funds	30	34	33	33
Domestic Mutual Funds	-	4	4	7
Foreign Investment Funds	-	3	2	2
Foreign Mutual Funds	992	962	1199	1314

Panel B. Average Across PFAs of the Percentage of Assets Held Relative to the Number of Assets Approved

	2002	2003	2004	2005
Domestic Equity	71.6%	64.9%	69.2%	65.5%
Domestic Investment Funds	74.3%	70.6%	73.2%	74.2%
Domestic Mutual Funds	-	0.0%	25.0%	52.4%
Foreign Investment Funds	-	33.3%	64.3%	50.0%
Foreign Mutual Funds	14.5%	18.0%	16.7%	16.1%

Table 5
Proportion of Assets Traded by the Entire Pension System

This table presents the average across time of the percentage of assets that are traded by all PFAs, overall and by asset class. Column (1) presents the average across all assets, column (2) only considers assets that are traded by more than one PFA, and column (3) only considers assets that are traded by more than half of the PFAs in operation at any point in time.

	Percentage of Assets Traded		
	All Assets	Assets Traded by More Than One PFA	Assets Traded by More Than Half of PFAs
	(1)	(2)	(3)
All Asset Classes	11.5%	3.3%	0.7%
Domestic Assets			
Former Pension System Bonds	7.1%	0.9%	0.0%
Corporate Bonds	17.7%	4.6%	0.8%
Financial Institutions	32.1%	6.3%	0.1%
Government Paper	21.3%	6.3%	0.4%
Investment and Mutual Funds	19.4%	4.6%	1.5%
Equity	56.7%	38.3%	12.9%
Mortgage Bonds	13.5%	6.2%	2.1%
Foreign Assets			
Fixed Income	30.8%	2.7%	0.1%
Investment and Mutual Funds	58.1%	23.6%	3.8%
Equity	28.2%	3.1%	0.0%

Table 6

Contemporaneous Herding

This table presents the average Lakonishok et al. (1992) herding statistic over all assets and by asset class. The herding statistic is calculated using the asset-specific probability of buying an asset at any point in time. Column (1) presents the results considering all assets, column (2) considers assets traded by more than one PFA, and column (3) considers assets traded by more than half of the PFAs in operation at any point in time. Numbers represent percentages (results are multiplied by 100). T-tests are two-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Standard errors are presented in parentheses. In addition, column (4) presents the average asset-specific probability of buying an asset, calculated over all assets and by asset class. The dashes in column (3) indicate that Foreign Equity is not traded by more than half of PFAs in operation.

	Herding Statistic			Average Probability of Buying an Asset
	All Assets	Assets Traded by More Than One PFA	Assets Traded by More Than Half of PFAs	
	(1)	(2)	(3)	(4)
All Asset Classes	2.26**	0.88**	1.77**	54.6%
	(0.03)	(0.04)	(0.09)	
Domestic Assets				
Former Pension System Bonds	-2.53**	-11.02**	2.07**	66.3%
	(0.04)	(0.08)	(0.29)	
Corporate Bonds	2.38**	5.04**	5.74**	53.4%
	(0.25)	(0.61)	(0.52)	
Financial Institutions	0.81**	1.86**	1.66**	73.5%
	(0.08)	(0.16)	(0.58)	
Government Paper	-0.10	-2.45**	2.73**	61.0%
	(0.07)	(0.15)	(0.42)	
Investment and Mutual Funds	2.41**	3.03**	1.35**	57.5%
	(0.61)	(1.25)	(0.56)	
Equity	0.96**	1.28**	0.66**	53.4%
	(0.18)	(0.24)	(0.25)	
Mortgage Bonds	8.84**	4.45**	0.92**	24.9%
	(0.06)	(0.06)	(0.11)	
Foreign Assets				
Fixed Income	-0.01	3.09**	15.60**	61.8%
	(0.23)	(1.00)	(5.14)	
Investment and Mutual Funds	1.43**	2.23**	1.51**	62.4%
	(0.12)	(0.21)	(0.28)	
Equity	-0.23	-0.32	-	67.2%
	(0.34)	(1.79)	-	

Table 7
Dynamic Herding

For each moment in time, we have run the regression of the probability of buying an instrument at a moment in time on the lagged probability of buying an instrument. This table presents the average coefficient across time, for all assets and by asset class. Column (1) presents the results considering all assets traded, column (2) considers assets traded by more than one PFA, and column (3) considers assets traded by more than half of the PFAs in operation at any point in time. Numbers represent percentages (results are multiplied by 100). T-tests are two-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. We have removed the asterisks on negative coefficients to facilitate the reading of the table. The standard error of this average coefficient is presented in parenthesis. In addition, this table presents the percentage of time coefficients that are positive at a ten-percent significance level and the percentage of time coefficients that are negative at a ten-percent significance level. The dashes in columns (2) and (3) indicate asset classes that are not traded by more than one PFA or not traded by more than half of PFAs in operation, respectively.

		Herding Regressions		
		All Assets	Assets Traded by More Than One PFA	Assets Traded by More Than Half of PFAs
		(1)	(2)	(3)
All Asset Classes	Average Coefficient	-33.65	7.20**	27.93**
	Standard Error	(0.91)	(1.57)	(4.01)
	% Positive Coefficients	0.00%	38.74%	36.89%
	% Negative Coefficients	100.00%	13.51%	4.85%
Domestic Assets				
Former Pension System Bonds	Average Coefficient	-58.66	-59.60	-
	Standard Error	(1.51)	(5.21)	-
	% Positive Coefficients	0.00%	0.00%	-
	% Negative Coefficients	99.10%	62.22%	-
Corporate Bonds	Average Coefficient	-18.83	-4.32	-
	Standard Error	(4.02)	(14.4)	-
	% Positive Coefficients	1.25%	13.04%	-
	% Negative Coefficients	33.75%	30.43%	-
Financial Institutions	Average Coefficient	-24.41	-11.81	-
	Standard Error	(1.89)	(4.88)	-
	% Positive Coefficients	2.73%	16.05%	-
	% Negative Coefficients	69.09%	20.99%	-
Government Paper	Average Coefficient	-31.67	-6.07	9.93
	Standard Error	(1.57)	(2.79)	(17.8)
	% Positive Coefficients	0.90%	8.18%	21.05%
	% Negative Coefficients	93.69%	20.91%	26.32%
Investment and Mutual Funds	Average Coefficient	-34.33	-	-
	Standard Error	(8.69)	-	-
	% Positive Coefficients	0.00%	-	-
	% Negative Coefficients	33.33%	-	-
Equity	Average Coefficient	22.39**	26.16**	34.10**
	Standard Error	(1.77)	(1.81)	(4.47)
	% Positive Coefficients	61.26%	59.46%	28.00%
	% Negative Coefficients	1.80%	0.90%	2.00%
Mortgage Bonds	Average Coefficient	-26.70	4.91	-
	Standard Error	(1.81)	(3.28)	-
	% Positive Coefficients	3.60%	28.16%	-
	% Negative Coefficients	85.59%	13.59%	-
Foreign Assets				
Fixed Income	Average Coefficient	-18.25	-13.27	-
	Standard Error	(4.04)	(24.9)	-
	% Positive Coefficients	2.41%	11.11%	-
	% Negative Coefficients	26.51%	33.33%	-
Investment and Mutual Funds	Average Coefficient	1.49	15.31**	15.89**
	Standard Error	(2.43)	(3.30)	(6.83)
	% Positive Coefficients	26.42%	37.11%	21.74%
	% Negative Coefficients	18.87%	7.22%	2.17%
Equity	Average Coefficient	-26.37	6.72	-
	Standard Error	(10.2)	(57.5)	-
	% Positive Coefficients	0.00%	0.00%	-
	% Negative Coefficients	13.64%	0.00%	-

Table 8
Average Percentage of Assets Traded by a PFA

This table presents several trading statistics during the entire sample period (July 1996 to December 2005). Column (1) presents the average percentage of assets that a PFA trades, as a share of the total amount of assets held in its portfolio, over all assets and by asset class. Column (2) presents the average across PFAs of the lagged weight of the traded portfolio. Column (3) presents the average across PFAs of the difference in weights (contemporaneous weight using lagged prices minus lagged weights) for the traded portfolio.

	Trading Statistics		
	Average Percentage of Assets Traded Relative to Assets Held	Average Lagged Weight of Traded Portfolio	Average Weight Difference of Traded Portfolio
	(1)	(2)	(3)
All Asset Classes	11.0%	21.7%	4.1%
Domestic Assets			
Former Pension System Bonds	5.9%	0.2%	0.0%
Corporate Bonds	7.2%	0.5%	0.1%
Financial Institutions	34.6%	1.9%	0.4%
Government Paper	9.5%	2.6%	0.8%
Investment and Mutual Funds	6.4%	0.1%	0.1%
Equity	37.4%	9.0%	1.4%
Mortgage Bonds	13.5%	3.3%	0.4%
Foreign Assets			
Fixed Income	37.2%	0.5%	0.2%
Investment and Mutual Funds	47.6%	4.2%	0.9%
Equity	54.2%	0.1%	0.0%

Table 9
Turnover Statistics on Fund Type Fixed Effects

This table presents the results of the regression of the turnover statistics at the PFA-time-fund-type level on PFA, time, and fund type fixed effects. The table only displays the overall mean and the zero-mean fixed effects for each fund type. The Grinblatt et al. (1995) and the Ferson and Khang (2002) turnover measures are calculated using weights with the contemporaneous price. Standard errors are presented in parentheses. T-tests are two-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Panel A considers the entire sample period (July 1996 to December 2005) and Panel B only considers the multi-fund period (September 2002 to December 2005), starting six months after it was implemented to avoid distortions. Numbers represent percentages (results are multiplied by 100).

Panel A. Turnover Statistics on Fund-Type Fixed Effects (1996-2005)

	Grinblatt et al.	Ferson and Khang
	(1)	(2)
Overall Mean	10.92**	10.36**
	(0.37)	(0.37)
Fund A	0.64*	0.68*
	(0.36)	(0.37)
Fund B	-0.73**	-0.87**
	(0.24)	(0.24)
Fund C	-5.52**	-5.75**
	(0.44)	(0.44)
Fund D	0.56	0.60
	(0.43)	(0.43)
Fund E	5.05**	5.33**
	(0.62)	(0.62)

Panel B. Turnover Statistics on Fund-Type Fixed Effects (2003-2005)

	Grinblatt et al.	Ferson and Khang
	(1)	(2)
Overall Mean	7.20**	6.47**
	(0.17)	(0.17)
Fund A	1.86**	1.91**
	(0.21)	(0.21)
Fund B	-0.64**	-0.80**
	(0.11)	(0.11)
Fund C	-2.00**	-2.17**
	(0.12)	(0.12)
Fund D	-0.10	-0.08
	(0.21)	(0.22)
Fund E	0.89**	1.14**
	(0.28)	(0.28)

Table 10
Turnover Statistics on Asset Class Fixed Effects

This table presents the results of the regression of turnover statistics at the PFA-time-fund-type-asset-class level on PFA, time, fund type, and asset class fixed effects. The table only displays the overall mean and the zero-mean fixed effects for each asset class. The Grinblatt et al. (1995) and the Ferson and Khang (2002) turnover measures are calculated using weights with contemporaneous price. Two alternative measures are presented, using overall weights or weights within asset class, alternatively. Standard errors are presented in parentheses. T-tests are two-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Panel A considers the entire sample period (July 1996 to December 2005) and Panel B only considers the multi-fund period (September 2002 to December 2005), starting six months after it was implemented to avoid distortions. Numbers represent percentages (results are multiplied by 100).

Panel A. Turnover Statistics on Asset-Class Fixed Effects (1996-2005)

	Using Overall Weights		*Using Within-Asset-Class Weights*	
	Grinblatt et al.	Ferson and Khang	Grinblatt et al.	Ferson and Khang
	(1)	(2)	(3)	(4)
Overall Mean	1.29**	1.23**	12.66**	11.78**
	(0.04)	(0.04)	(0.28)	(0.28)
Domestic Assets				
Former Pension System Bonds	-0.27**	-0.21**	-3.58**	-2.83**
	(0.04)	(0.04)	(0.30)	(0.31)
Corporate Bonds	-0.52**	-0.49**	-5.24**	-4.99**
	(0.02)	(0.02)	(0.24)	(0.25)
Financial Institutions	0.34**	0.38**	0.55**	1.40**
	(0.05)	(0.05)	(0.26)	(0.26)
Government Paper	2.14**	2.06**	0.34**	0.82**
	(0.14)	(0.14)	(0.32)	(0.33)
Investment and Mutual Funds	-0.46**	-0.41**	-6.59**	-6.22**
	(0.01)	(0.01)	(0.25)	(0.24)
Equity	0.33**	0.15**	-5.20**	-5.34**
	(0.02)	(0.02)	(0.23)	(0.23)
Mortgage Bonds	-0.06**	-0.06**	-4.46**	-3.97**
	(0.04)	(0.04)	(0.29)	(0.30)
Foreign Assets				
Fixed	-0.41**	-0.39**	4.80**	4.68**
	(0.02)	(0.02)	(0.55)	(0.52)
Investment and Mutual Funds	1.07**	1.01**	0.40**	0.73**
	(0.04)	(0.04)	(0.29)	(0.29)
Equity	-0.57**	-0.52**	-2.68**	-2.36**
	(0.04)	(0.04)	(0.80)	(0.79)

Panel B. Turnover Statistics on Asset-Class Fixed Effects (2003-2005)

	Using Overall Weights		*Using Within-Asset-Class Weights*	
	Grinblatt et al.	Ferson and Khang	Grinblatt et al.	Ferson and Khang
	(1)	(2)	(3)	(4)
Overall Mean	0.68**	0.61**	10.34**	9.60**
	(0.01)	(0.01)	(0.20)	(0.20)
Domestic Assets				
Former Pension System Bonds	-0.40**	-0.34**	-5.19**	-4.51**
	(0.01)	(0.01)	(0.30)	(0.30)
Corporate Bonds	-0.35**	-0.33**	-5.39**	-4.97**
	(0.01)	(0.01)	(0.26)	(0.27)
Financial Institutions	0.62**	0.65**	-0.21**	0.58**
	(0.03)	(0.03)	(0.30)	(0.30)
Government Paper	1.07**	1.01**	0.56**	0.98**
	(0.07)	(0.07)	(0.42)	(0.43)
Investment and Mutual Funds	-0.47**	-0.42**	-6.43**	-6.10**
	(0.01)	(0.01)	(0.33)	(0.33)
Equity	0.28**	0.12**	-5.90**	-6.24**
	(0.02)	(0.03)	(0.28)	(0.28)
Mortgage Bonds	-0.30**	-0.29**	-5.61**	-5.17**
	(0.01)	(0.01)	(0.28)	(0.28)
Foreign Assets				
Fixed	-0.25**	-0.22**	6.14**	5.93**
	(0.02)	(0.02)	(0.72)	(0.69)
Investment and Mutual Funds	1.56**	1.47**	-2.28**	-1.87**
	(0.05)	(0.05)	(0.28)	(0.28)
Equity	-0.56**	-0.50**	-4.81**	-4.38**
	(0.02)	(0.02)	(0.76)	(0.77)

Table 11
Proportion of Units Bought and Held Until Expiration

This table presents two statistics per asset class: (i) the average proportion of units of a given security that a PFA incorporates into its portfolio in its first purchase, and (ii) the proportion of the units of that security that a PFA liquidates at the security's maturity date; both measures are relative to the maximum number of units of that security that the PFA holds in its portfolio at any time. This table presents the average of both ratios across all instruments for each asset class, averaged across PFAs. The standard deviation of the ratios across PFAs is also presented.

	Ratio of Units at First Purchase to Maximum Units in Portfolio		Ratio of Units at Expiration to Maximum Units in Portfolio	
	Average	Standard Deviation	Average	Standard Deviation
	(1)	(2)	(3)	(4)
Domestic Assets				
Former Pension System Bonds	0.96	0.05	0.98	0.05
Corporate Bonds	0.97	0.05	0.98	0.06
Financial Institutions	0.98	0.01	0.95	0.05
Government Paper	0.91	0.08	0.93	0.07
Mortgage Bonds	0.96	0.04	0.85	0.13
Foreign Assets				
Fixed Income	0.93	0.04	0.97	0.05

Table 12
Sias Momentum Regressions

This table presents the results of the regression of the fraction of funds buying a given asset at a moment in time on the contemporaneous rate of return and the lagged rate of return, alternatively and combined. The first specification (columns 1 to 4) takes into account all assets and the second specification (columns 5 to 8) only considers assets that are traded by more than one PFA at a moment in time. These regressions are presented over all asset classes and by asset class. Standard errors are presented in parenthesis. T-tests are two-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level.

	Using Lagged Return and Return Alternatively as Independent Variables				*Using Both Lagged Return and Return as Independent Variables*			
	All Assets		Assets Traded by More than One PFA		All Assets		Assets Traded by More than One PFA	
	Lagged Return	Return	Lagged Return	Return	Lagged Return	Return	Lagged Return	Return
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All Asset Classes	0.10	1.97**	-0.12	1.70**	0.28**	2.06**	0.00	1.63**
	(0.11)	(0.10)	(0.15)	(0.13)	(0.10)	(0.10)	(0.14)	(0.13)
Domestic Assets								
Former Pension System Bonds	1.88**	2.53**	1.34**	0.93**	2.58**	3.06**	1.83**	1.48**
	(0.69)	(0.52)	(0.52)	(0.33)	(0.69)	(0.51)	(0.57)	(0.38)
Corporate Bonds	0.32*	0.15	0.07	1.19**	0.35*	0.17	0.15	1.34**
	(0.17)	(0.17)	(0.27)	(0.56)	(0.18)	(0.17)	(0.33)	(0.55)
Financial Institutions	-0.28	0.06	0.82*	-0.14	-0.29	-0.04	0.81**	-0.08
	(0.23)	(0.28)	(0.43)	(0.49)	(0.23)	(0.26)	(0.45)	(0.48)
Government Paper	0.34**	0.49**	0.49**	0.49**	0.38**	0.47**	0.55**	0.47**
	(0.08)	(0.08)	(0.12)	(0.11)	(0.08)	(0.08)	(0.12)	(0.11)
Investment and Mutual Funds	-0.57	0.55	1.22	1.94	-0.85	0.83	0.80	1.23
	(0.69)	(0.62)	(1.49)	(1.79)	(0.70)	(0.67)	(1.39)	(1.73)
Equity	0.26**	-0.09*	0.27**	-0.19**	0.26**	-0.10*	0.27**	-0.20**
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Mortgage Bonds	-1.70**	1.53**	-2.67**	0.69**	-1.31**	1.30**	-2.41**	0.55**
	(0.09)	(0.10)	(0.36)	(0.08)	(0.09)	(0.09)	(0.37)	(0.06)
Foreign Assets								
Fixed Income	-0.03	0.09	0.03	0.01	0.42	-0.09	-0.03	-0.38
	(0.35)	(0.25)	(0.81)	(0.84)	(0.38)	(0.42)	(0.80)	(0.98)
Investment and Mutual Funds	0.98**	0.61**	0.88**	0.73**	0.93**	0.57**	0.83**	0.64**
	(0.11)	(0.15)	(0.11)	(0.21)	(0.10)	(0.15)	(0.10)	(0.21)
Equity	0.39*	-0.53**	0.38	-0.31	0.26	-0.55**	0.43	-0.24
	(0.21)	(0.10)	(1.91)	(0.31)	(0.23)	(0.11)	(2.00)	(0.39)

Table 13
Momentum Statistics

This table presents the average momentum statistics across PFAs and the percentage of PFAs that are momentum or contrarian traders at a ten-percent significance level. Three momentum statistics are presented: the Grinblatt et al. (1995) statistic, the Ferson & Khang (2002) statistic, and the Kaminsky et al. (2004) statistic. These statistics are calculated using contemporaneous and lagged prices, alternatively. T-tests are one-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Standard errors are presented in parenthesis. Numbers represent percentages because the averages and standard errors are multiplied by 100 in the case of the Kaminsky et al. measure (returns are in percentages) and by 10,000 in the case of the other measures (weights and returns are in percentages). In addition, t-tests are computed for each PFA and momentum statistic in order to calculate the percentage of PFAs that are momentum or contrarian traders at a ten-percent significance level.

		Lagged Momentum Statistics			Contemporaneous Momentum Statistics		
		L1M Grinblatt et al.	LM1 Ferson and Khang	M1 Kaminsky et al.	L0M Grinblatt et al.	LM0 Ferson and Khang	M0 Kaminsky et al.
		(1)	(2)	(3)	(4)	(5)	(6)
All Asset Classes	Average Statistic	3.16**	3.89**	53.39**	22.0**	-4.77**	177.4**
	% Momentum Traders	37.50%	0.54%	0.50%	0.96%	0.13%	0.75%
	% Contrarian Traders	0.00%	0.00%	0.04%	0.00%	0.04%	0.00%
Domestic Assets							
Former Pension System Bonds	Average Statistic	0.01	0.01	31.93**	0.08**	0.00	31.83**
	% Momentum Traders	13.04%	0.22%	0.41%	0.61%	0.39%	0.39%
	% Contrarian Traders	8.70%	0.17%	0.09%	0.00%	0.13%	0.04%
Corporate Bonds	Average Statistic	0.08	0.24**	0.83	1.03**	-0.02	-1.05
	% Momentum Traders	0.00%	0.21%	0.17%	0.92%	0.04%	0.13%
	% Contrarian Traders	16.67%	0.00%	0.04%	0.00%	0.21%	0.17%
Financial Institutions	Average Statistic	-0.00	-0.00	1.82**	0.39**	0.04	3.70**
	% Momentum Traders	33.3%	0.2%	0.5%	0.7%	0.3%	0.5%
	% Contrarian Traders	29.2%	0.3%	0.1%	0.1%	0.3%	0.1%
Government Paper	Average Statistic	0.22	0.76**	9.39**	5.35**	0.97**	14.72**
	% Momentum Traders	16.67%	0.29%	0.38%	0.92%	0.50%	0.38%
	% Contrarian Traders	29.17%	0.00%	0.00%	0.00%	0.04%	0.00%
Investment and Mutual Funds	Average Statistic	-0.05	-0.15*	-1.01*	0.30**	-0.00	-0.01
	% Momentum Traders	29.17%	0.04%	0.05%	0.83%	0.00%	0.13%
	% Contrarian Traders	0.00%	0.08%	0.05%	0.00%	0.04%	0.04%
Equity	Average Statistic	2.71**	2.44**	23.20**	10.3**	-6.81**	-13.8**
	% Momentum Traders	33.33%	0.21%	0.63%	0.88%	0.08%	0.00%
	% Contrarian Traders	0.00%	0.00%	0.00%	0.00%	0.21%	0.33%
Mortgage Bonds	Average Statistic	-0.28**	0.07*	-19.8**	1.54**	0.42**	133.3**
	% Momentum Traders	0.00%	0.17%	0.00%	0.88%	0.71%	0.75%
	% Contrarian Traders	58.33%	0.13%	0.29%	0.00%	0.00%	0.00%
Foreign Assets							
Fixed Income	Average Statistic	0.10**	0.14**	0.85	0.46**	-0.02	0.66
	Momentum Traders	16.67%	0.25%	0.25%	0.42%	0.17%	0.25%
	Contrarian Traders	0.00%	0.00%	0.00%	0.00%	0.33%	0.25%
Investment and Mutual Funds	Average Statistic	0.69*	0.63*	10.35**	2.62**	0.86**	11.78**
	Momentum Traders	50.00%	0.55%	0.53%	0.90%	0.50%	0.42%
	Contrarian Traders	5.00%	0.10%	0.00%	0.00%	0.10%	0.05%
Equity	Average Statistic	0.04**	0.04*	1.66*	0.15**	0.03*	-1.09
	Momentum Traders	0.00%	0.10%	0.00%	0.60%	0.20%	0.00%
	Contrarian Traders	0.00%	0.00%	0.00%	0.00%	0.00%	0.20%

Table 14
Effect of Past Trading on Future Prices

This table presents the results of the regression of the rate of return on the lagged fraction of funds buying an asset at a moment in time. The regression is carried out over all asset classes and for each asset class separately. Standard errors are presented in parentheses. T-tests are one-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Numbers represent percentages (results are multiplied by 100).

	Lagged Fraction of Funds Buying
All Asset Classes	0.10
	(0.12)
Domestic Assets	
Former Pension System Bonds	-0.00
	(0.07)
Corporate Bonds	0.17
	(0.16)
Financial Institutions	0.04*
	(0.02)
Government Paper	0.33**
	(0.08)
Investment and Mutual Funds	0.46*
	(0.28)
Equity	-0.06
	(0.35)
Mortgage Bonds	-0.82**
	(0.08)
Foreign Assets	
Fixed Income	0.14
	(0.47)
Investment and Mutual Funds	0.39**
	(0.12)
Equity	-0.82**
	(0.35)

Table 15
Does Momentum Explain Herding?

This table presents the results of the regression of the herding statistic which uses the asset-specific probability of buying an asset, on a constant and the lagged rate of return. The regressions are carried out over all asset classes and for each asset class separately. Standard errors are presented in parenthesis. T-tests are one-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Numbers represent percentages (results are multiplied by 100).

	Lagged Return
All Asset Classes	-25.36**
	(1.20)
Domestic Assets	
Former Pension System Bonds	-18.38**
	(2.14)
Corporate Bonds	-6.54
	(5.48)
Financial Institutions	2.11
	(12.3)
Government Paper	-4.08**
	(1.91)
Investment and Mutual Funds	-3.00
	(6.02)
Equity	-0.93
	(1.98)
Mortgage Bonds	-37.11**
	(2.14)
Foreign Assets	
Fixed Income	-5.64
	(7.79)
Investment and Mutual Funds	-0.48
	(2.49)
Equity	12.93*
	(9.24)

Table 16
Dynamic Herding Regressions

This table presents the results of two regressions: (i) the typical Sias (2004) herding regression, that is, the regression of the fraction of funds buying a given asset at a moment in time on the lagged fraction of funds buying, and (ii) the same regression adding the lagged rate of return as an additional regressor. The objective is to analyze if herding is driven by momentum. Both regressions are carried out over all asset classes and for each asset class separately. Standard errors are presented in parentheses. T-tests are two-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level.

		Using Both as Independent Variables	
	Lagged Fraction of Funds Buying	Lagged Fraction of Funds Buying	Lagged Return
	(1)	(2)	(3)
All Asset Classes	-0.31**	-0.34**	-0.05
	(0.00)	(0.00)	(0.06)
Domestic assets			
Former Pension System Bonds	1.73**	-0.42**	1.17**
	(0.66)	(0.01)	(0.41)
Corporate Bonds	-0.28*	-0.21**	-0.43**
	(0.17)	(0.02)	(0.14)
Financial Institutions	0.01	-0.41**	-0.58
	(0.33)	(0.03)	(0.36)
Government Paper	0.26**	-0.31**	-0.12
	(0.09)	(0.01)	(0.10)
Investment and Mutual Funds	0.61	-0.34**	-0.33
	(0.49)	(0.06)	(0.68)
Equity	0.16**	0.23**	0.11
	(0.07)	(0.01)	(0.07)
Mortgage Bonds	-1.48**	-0.34**	-1.29**
	(0.12)	(0.01)	(0.09)
Foreign assets			
Fixed Income	0.98**	-0.19**	0.77*
	(0.28)	(0.03)	(0.42)
Investment and Mutual Funds	0.49**	-0.00	0.50**
	(0.12)	(0.02)	(0.12)
Equity	-0.20	-0.16*	0.36
	(0.19)	(0.09)	(0.67)

Table 17
Herding Statistic on Fund Type Fixed Effects

This table presents the results of the regression of the asset-specific herding statistic on fund-type fixed effects. The herding statistic is calculated using an asset-specific probability of buying an asset at a moment in time. The regressions are calculated over all assets and by asset class. The table presents in different columns the overall mean and the zero-mean fixed effects for each fund type. T-tests are two-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. The standard error from the significance t-test is presented in parentheses. Numbers represent percentages (results are multiplied by 100).

	Overall Mean	Fund A	Fund B	Fund C	Fund D	Fund E
	(1)	(2)	(3)	(4)	(5)	(6)
All Asset Classes	0.79**	-0.57**	-0.09*	1.07**	-0.02	-0.37**
	(0.06)	(0.06)	(0.05)	(0.03)	(0.05)	(0.06)
Domestic Assets						
Former Pension System Bonds	-0.24**	0.22	0.26**	-0.78**	0.14	0.15
	(0.19)	(0.19)	(0.11)	(0.06)	(0.09)	(0.11)
Corporate Bonds	2.15**	-0.98*	0.14	1.41**	-0.34	-0.23
	(0.55)	(0.55)	(0.38)	(0.28)	(0.32)	(0.33)
Financial Institutions	0.61**	-0.00	-0.04	0.13	-0.06	-0.02
	(0.17)	(0.17)	(0.16)	(0.10)	(0.17)	(0.16)
Government Paper	0.53**	-0.10	0.20	0.36**	-0.11	-0.35**
	(0.30)	(0.30)	(0.18)	(0.11)	(0.16)	(0.15)
Investment and Mutual Funds	0.51	0.07	0.33	0.27	-0.76	0.07
	(0.46)	(0.46)	(0.63)	(0.52)	(0.62)	(0.46)
Equity	-0.47**	-0.59**	-0.36	0.96**	-0.47	0.47**
	(0.24)	(0.24)	(0.25)	(0.18)	(0.29)	(0.11)
Mortgage Bonds	2.38**	-1.77**	-0.62**	3.86**	-0.21**	-1.25**
	(0.16)	(0.16)	(0.10)	(0.06)	(0.10)	(0.11)
Foreign Assets						
Fixed Income	-0.16	-0.13	-0.12	-0.06	0.12	0.19
	(0.51)	(0.51)	(0.44)	(0.31)	(0.40)	(0.44)
Investment and Mutual Funds	0.91**	0.16	-0.17	-0.11	-0.04	0.16
	(0.15)	(0.15)	(0.20)	(0.17)	(0.25)	(0.15)
Equity	-0.08	0.27	0.11	-0.23	-0.44	0.27
	(0.64)	(0.64)	(0.52)	(0.60)	(0.96)	(0.64)

Table 18
Momentum Statistics on Fund-Type Fixed Effects

This table presents the results of the regressions of momentum statistics at the PFA-time-fund-type level on PFA, time, and fund type fixed effects, for the multi-fund period. Three momentum statistics are presented: the Grinblatt et al. (1995), the Ferson and Khang (2002), and the Kaminsky et al. (2004) measures. The lagged version of these statistics is presented, and weights with the contemporaneous price are used. The Grinblatt et al. (1995) momentum is also calculated using weights with the lagged price. Panel A presents the fund type fixed effects resulting from the regression of the momentum statistics on time and fund type fixed effects and Panel B presents the fund type fixed effects resulting from regressions that also include asset class fixed effects. Standard errors are presented in parentheses. T-tests are one-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Coefficients and standard errors are multiplied by 100.

Panel A. Momentum Statistics on PFA, Time, and Fund-Type Fixed Effects

	Using Weights With Contemporaneous Price			*Using Weights With Lagged Price*
	L1M	LM1	M1	L1M_lp
	Grinblatt et al.	Ferson and Khang	Kaminsky et al.	Grinblatt et al.
	(1)	(2)	(3)	(4)
Fund A	-2.85**	-2.32**	8.08**	1.05**
	(1.13)	(1.11)	(15.15)	(1.21)
Fund B	0.51**	0.56**	-103.54**	1.51**
	(0.73)	(0.71)	(58.83)	(0.76)
Fund C	1.11**	1.04**	122.65**	0.56**
	(0.57)	(0.57)	(95.00)	(0.58)
Fund D	0.88**	0.63**	-56.19**	-0.38**
	(0.84)	(0.83)	(41.54)	(0.83)
Fund E	0.32**	0.07**	29.0**	-2.76**
	(0.97)	(0.88)	(18.00)	(0.97)

Panel A. Momentum Statistics on PFA, Time, Fund-Type, and Asset-Class Fixed Effects

	Using Weights With Contemporaneous Price			*Using Weights With Lagged Price*
	L1M	LM1	M1	L1M_lp
	Grinblatt et al.	Ferson and Khang	Kaminsky et al.	Grinblatt et al.
	(1)	(2)	(3)	(4)
Fund A	-0.25**	-0.20**	-0.17	0.04
	(0.09)	(0.09)	(1.309)	(0.09)
Fund B	0.04	0.04	-9.37**	0.08
	(0.06)	(0.06)	(4.91)	(0.06)
Fund C	0.11**	0.10*	10.1	0.00
	(0.06)	(0.06)	(8.17)	(0.06)
Fund D	0.07	0.04	-5.38*	-0.08
	(0.07)	(0.07)	(3.40)	(0.07)
Fund E	0.02	0.01	4.82**	-0.04
	(0.10)	(0.10)	(2.16)	(0.10)

Figure 1

Number of PFAs and Funds

This figure shows the number of PFAs and pension funds in Chile for the entire sample period (July 1996 to December 2005). Significant regulatory modifications are marked on the figure, such as the introduction of Fund 2 in March 2000 and the introduction of the multi-fund regime in September 2002.

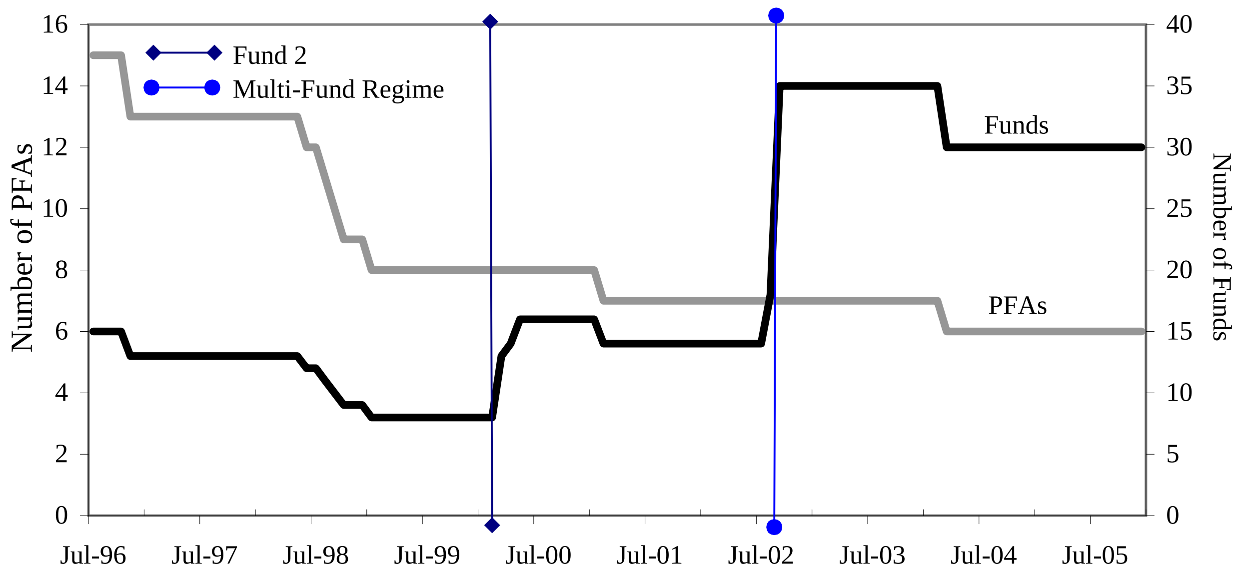


Figure 2
Evolution of PFA Holdings

This figure presents the total value (in billion of Chilean pesos) of assets under management for each PFA in operation during the sample period (July 1996 to December 2005). We consider each PFA resulting from a merger or acquisition as a new PFA. Therefore, Provida3 represents the merger of Provida with Proteccion and Provida4 represents the merger of Provida with Magister. For simplification, only the most important PFAs are explicitly indicated on the graph.

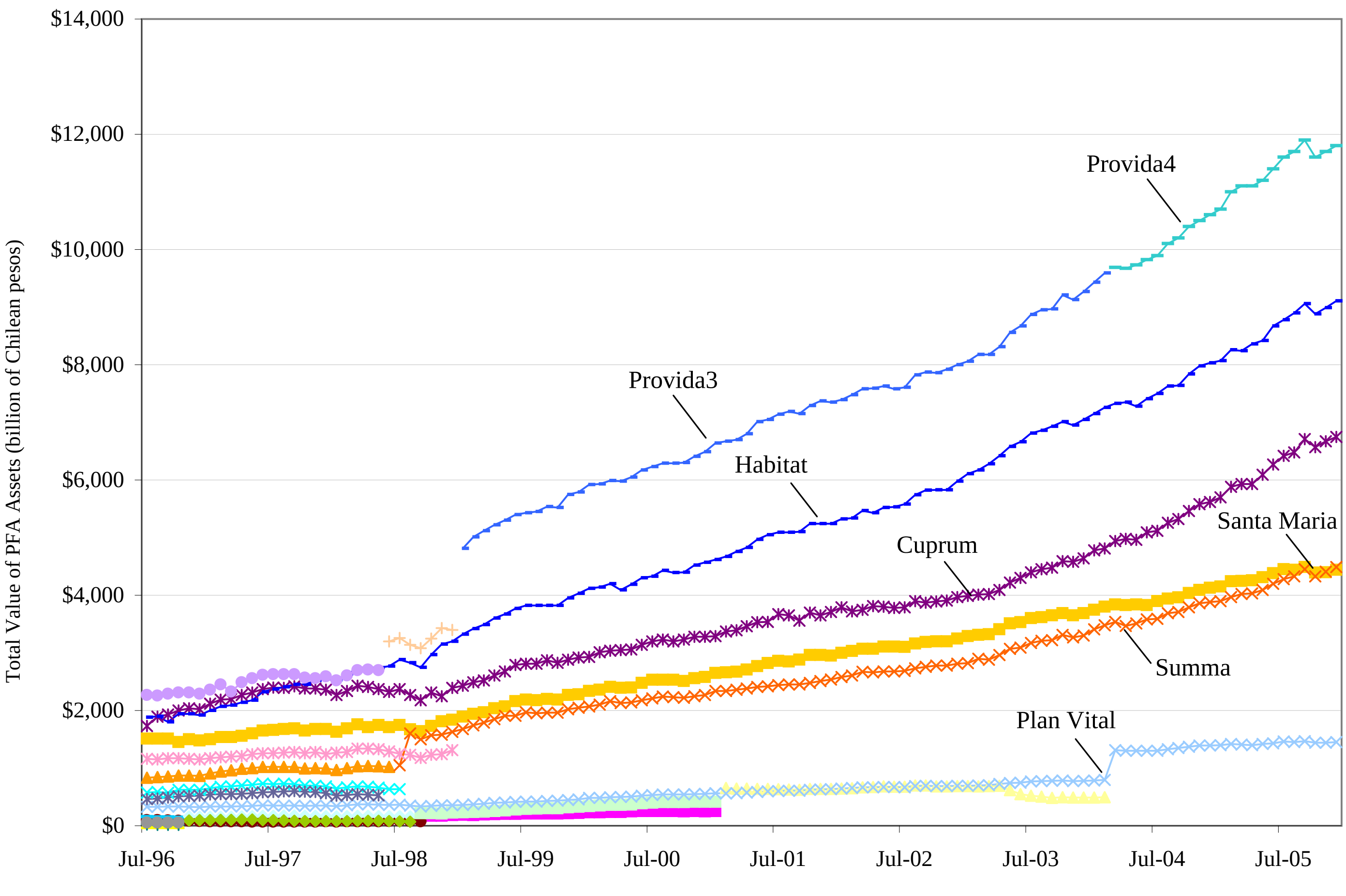


Figure 3

Pension System Holdings as a Share of GDP

This figure shows the size of total assets of pension funds across all PFAs relative to Chile's GDP by fund type for the entire sample period (July 1996 to December 2005), as of December of each year. The fund types reflect different risk profiles, from the riskiest fund (Fund A) to the most conservative fund (Fund E). The nominal values for December of each year are deflated using the GDP deflator.

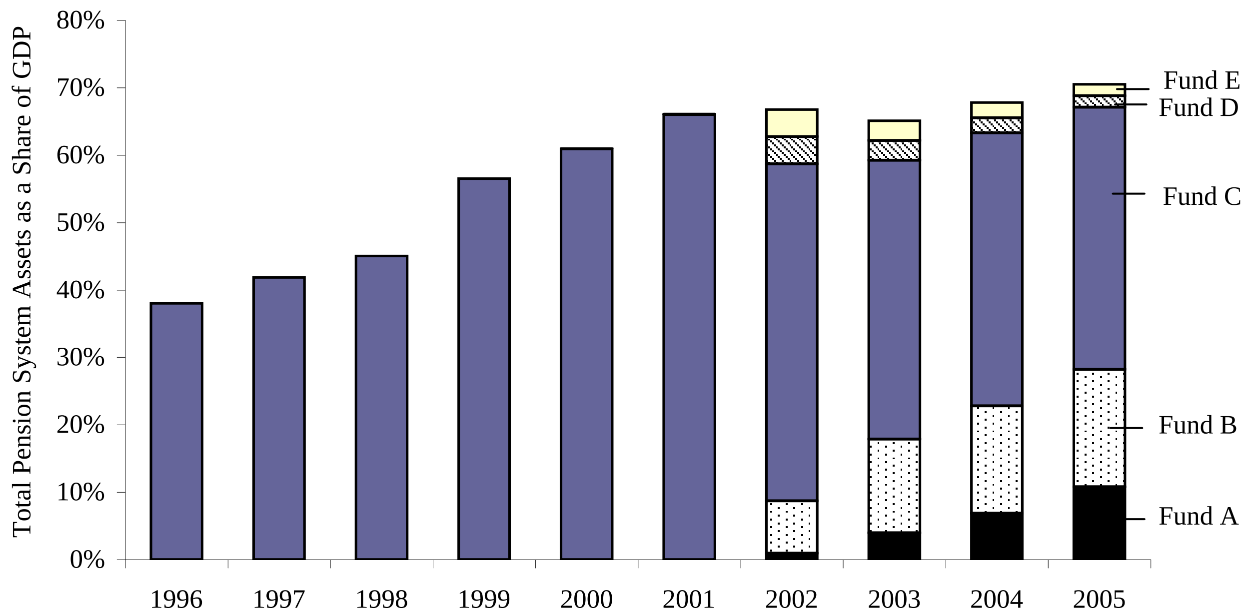


Figure 4
Relative Size of Fund Types in Pension System

This figure shows the relative size of fund tyes over all pension system holdings for the multi-fund period (September 2002 to December 2005). After the implementation of the multi-fund system, affiliates that did not choose a fund until October 29, 2002 were automatically assigned to a fund based on their age. Affiliates that were enrolled in Fund 2 and did not chose a new fund were automatically assigned to Fund E. This automatic allocation process ended in November 2003, when the Figure shows an important decline in the relative size of Fund C. The automatic allocation is as follows: (i) men and women under 35 years of age were assigned to Fund B, (ii) men older than 35 but younger than 55 years-old and women older than 35 but younger than 50 years-old were assigned to Fund C, and (iii) men older than 55 years-old and women older than 50 years-old were assigned to Fund D.

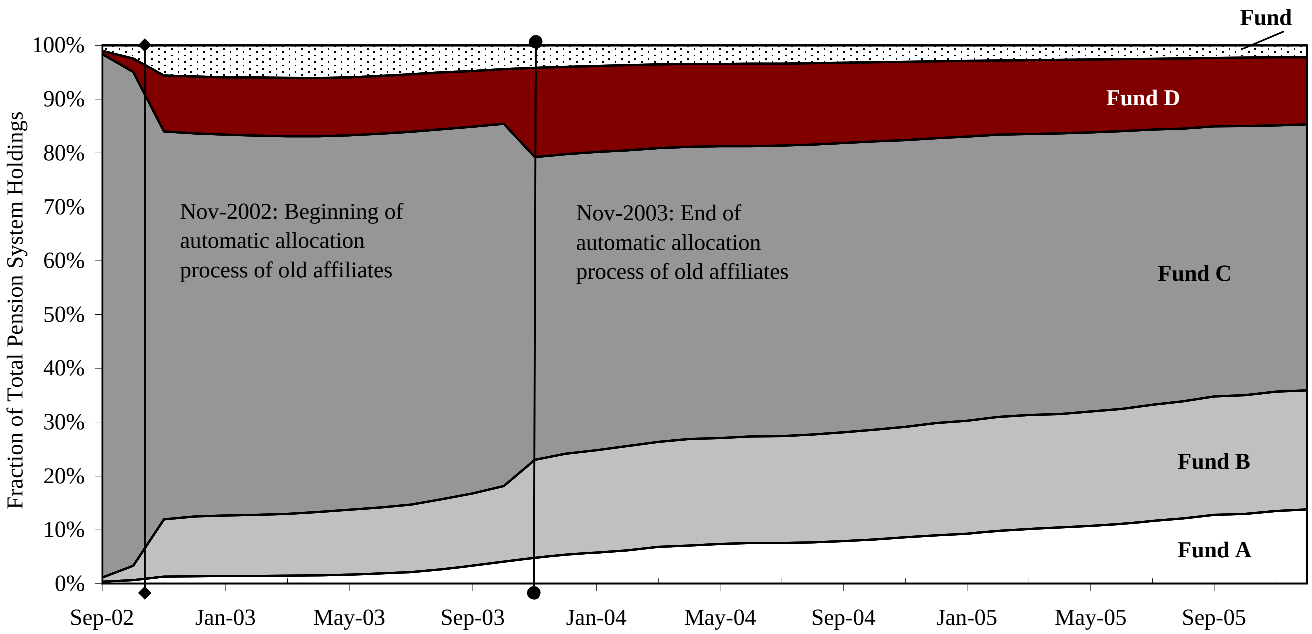
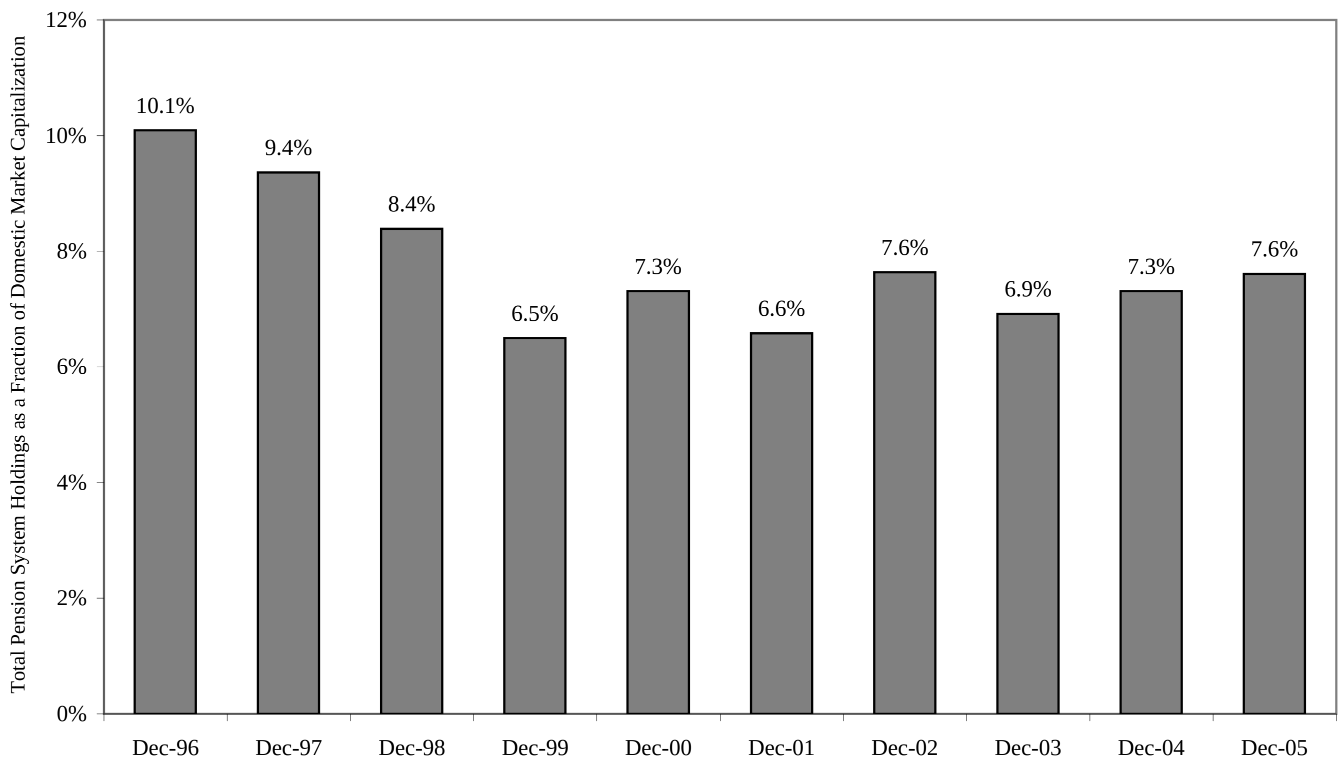


Figure 5

Pension System Equity Holdings as a Share of Domestic Market Capitalization

This figure shows the size of pension funds' investments in equities across PFAs relative to Chile's domestic equity market capitalization, as a percentage, for the entire sample period (July 1996 to December 2005), as of December of each year.



Source: World Bank Financial Development Indicators for domestic market capitalization.

Figure 6

Pension System Holdings in Domestic Assets

This figure shows the allocation of the pension fund system as a whole by asset class for the entire sample period (July 1996 to December 2005) as a percentage of total pension system investments in domestic instruments.

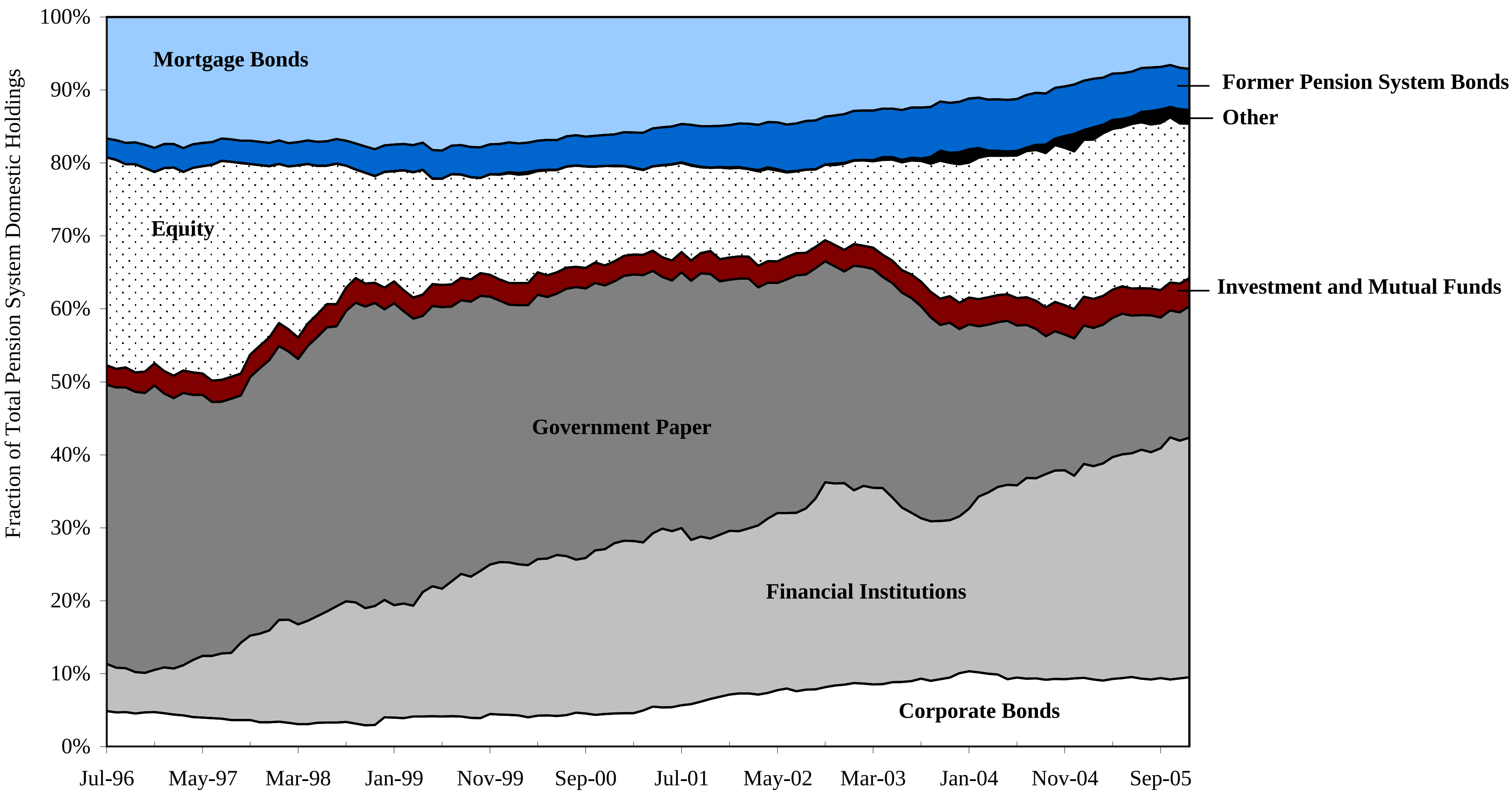
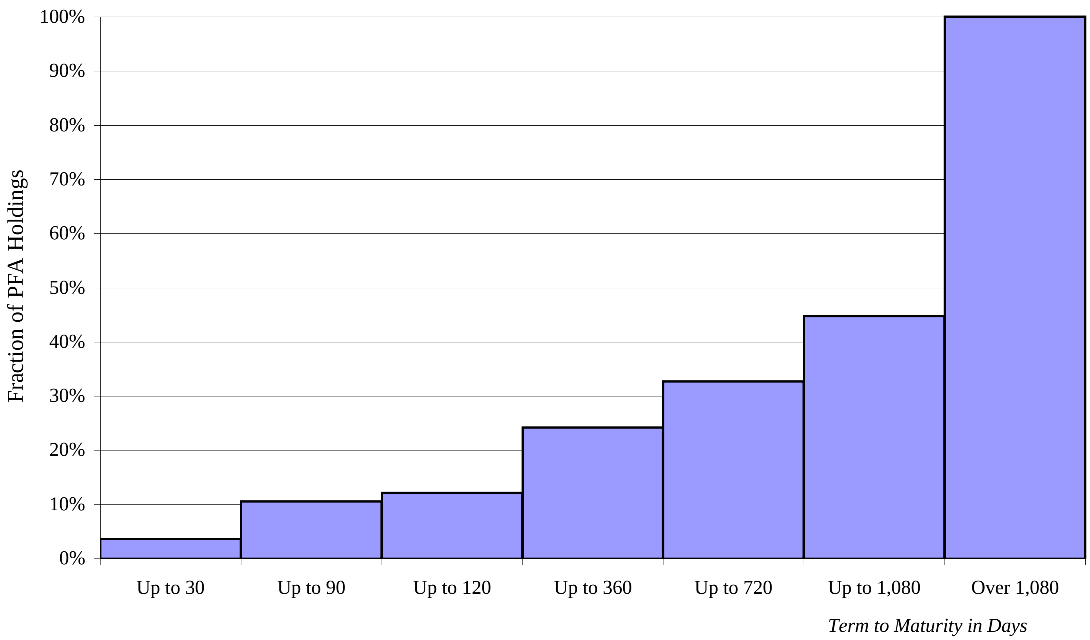


Figure 7
Maturity Structure of PFA Portfolios

This figure presents the average across PFAs of the accumulated fraction of the portfolio invested at different terms to maturity. Panel A presents the average across time for the sample period (July 1996 to December 2005). Panel B presents the results for December 2005.

Panel A. Average Fraction of PFA Portfolio Invested (1996 - 2005)



Panel B. Average Fraction of PFA Portfolio Invested (December 2005)

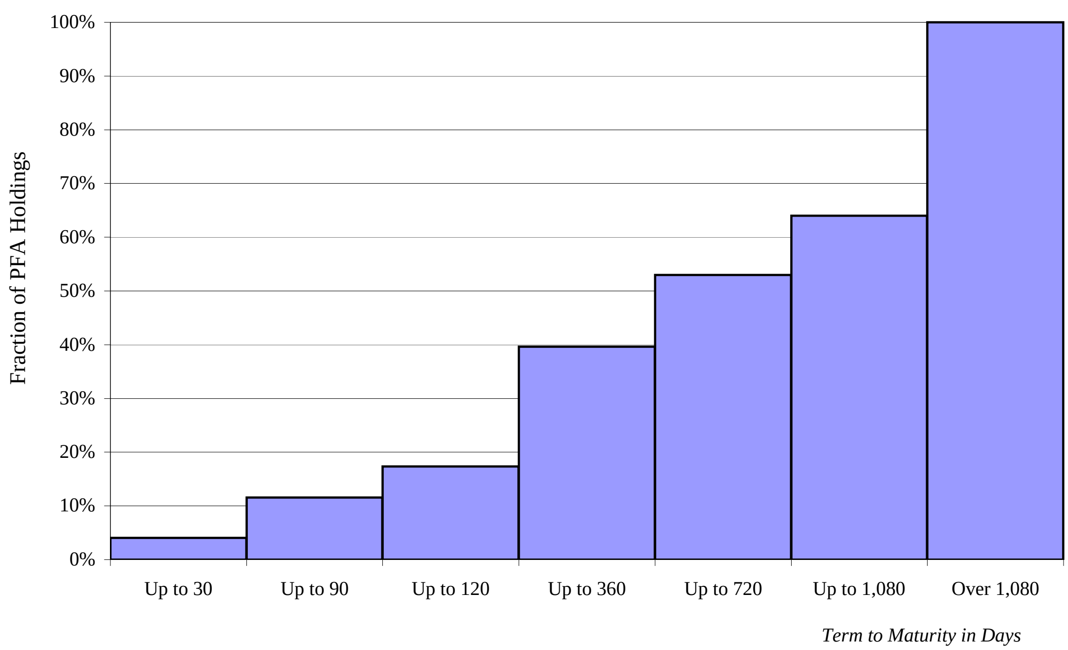


Figure 8

Pension System Allocation in Domestic and Foreign Assets

This figure shows the asset allocation of the pension system as a whole in domestic and foreign instruments for the entire sample period (July 1996 to December 2005). Allocation in foreign assets has increased. The major constraint for asset allocation of pension funds in foreign instruments has been quantitative limits imposed by the Central Bank of Chile according to the pension law (straight line shown on figure).

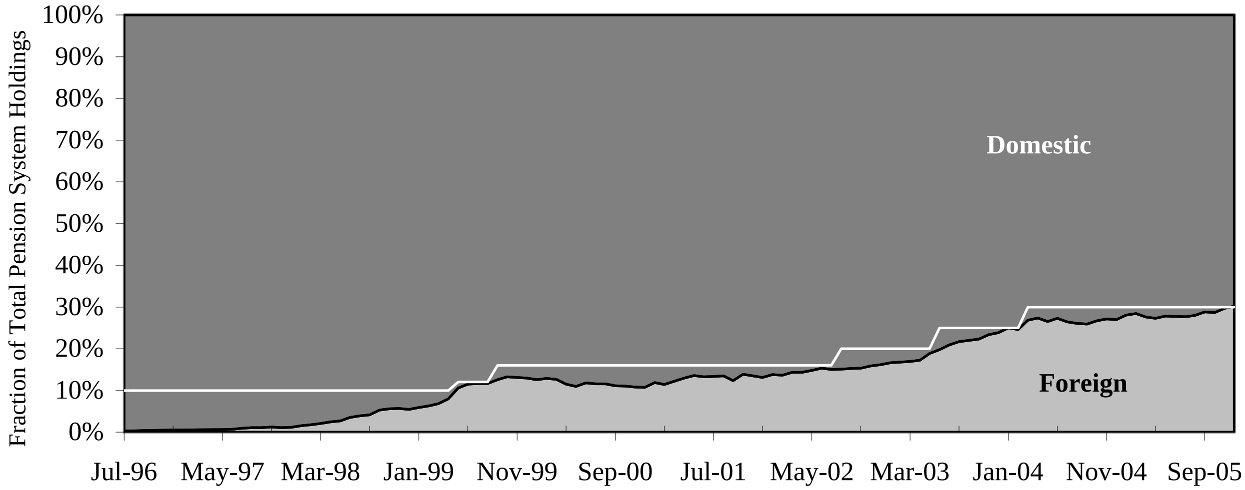


Figure 9

Pension System Allocation by Broad Asset Class

This figure shows the asset allocation of the pension system as a whole in four broad asset classes, as a percentage, for the entire sample period (July 1996 to December 2005). Whereas asset allocation in the domestic market has been mostly through fixed-income instruments, allocation in foreign investments has mostly been through variable-income instruments.

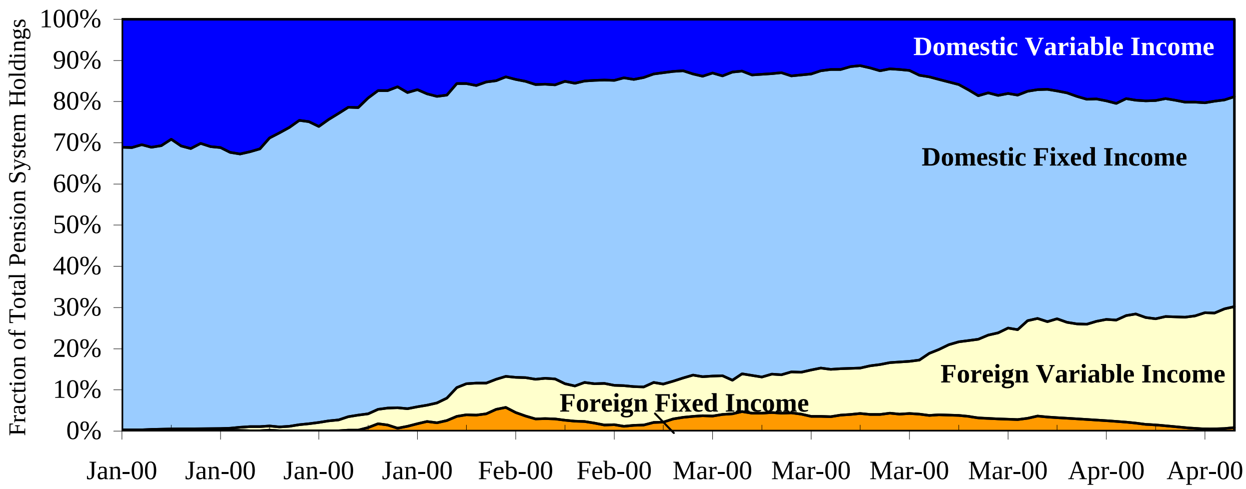


Figure 10

Pension System Holdings in Foreign Assets

This figure shows the allocation of the pension fund system as a whole by asset class, for the entire sample period (July 1996 to December 2005) as a percentage of the total investments in foreign instruments.

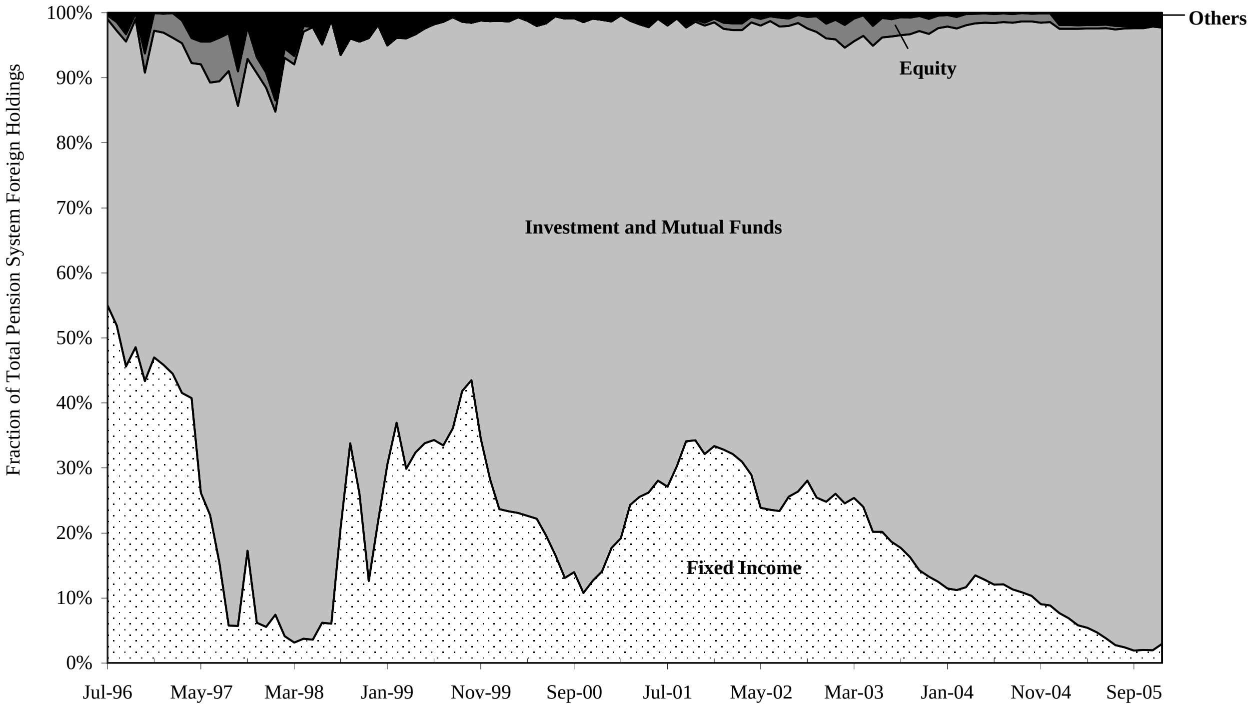


Figure 11

Portfolio Composition by Fund Type and Asset Class

This figure shows the portfolio composition of Chilean pension funds by fund type and asset class. The asset allocation of the different funds is generally consistent with the objectives of the multi-fund scheme.

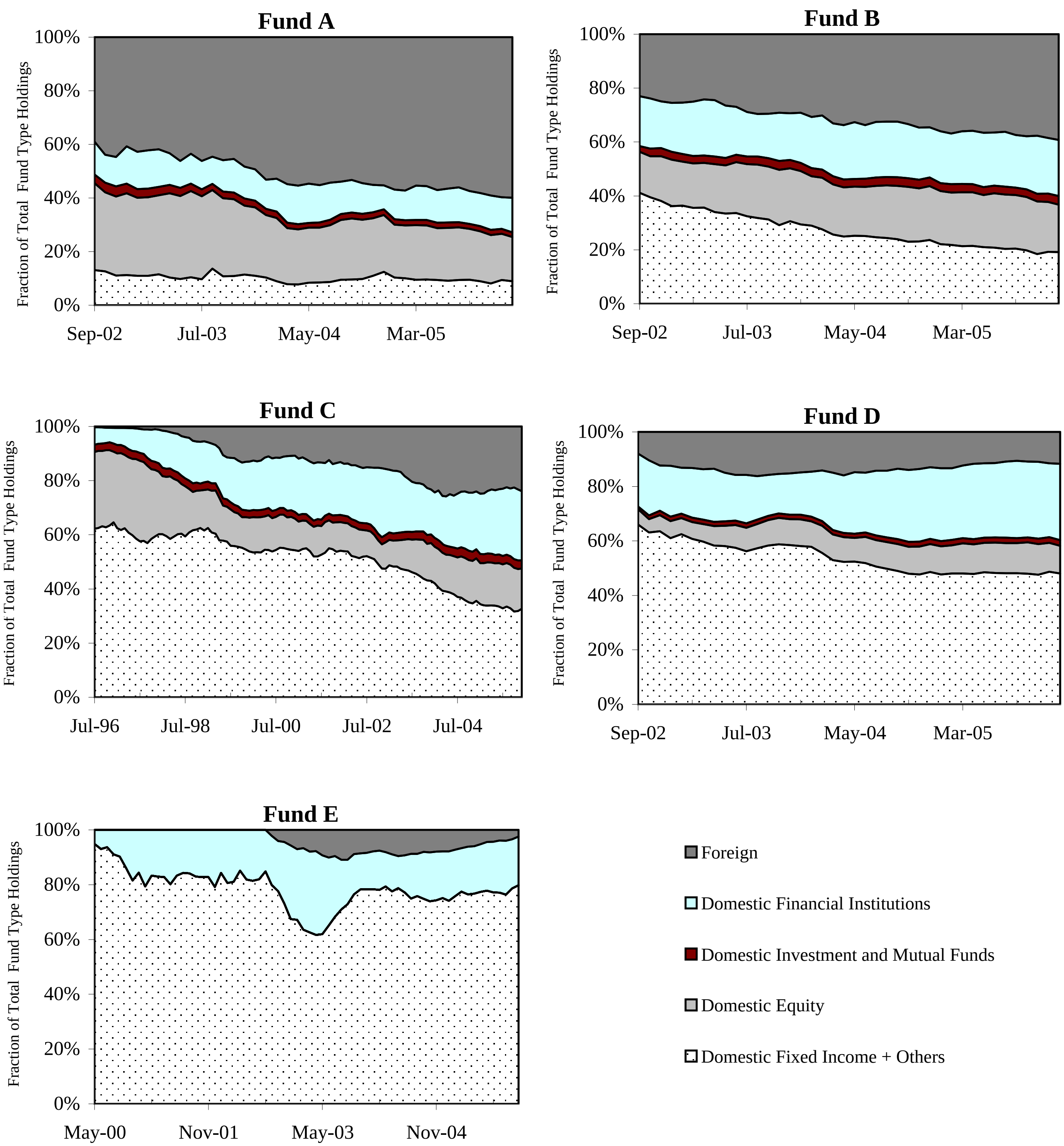


Figure 12

Pension System Holdings in Foreign Assets by Country

This figure shows the allocation of pension funds across all PFAs by country for the entire sample period (July 1996 to December 2005) as a percentage of total investments in foreign assets. NA refers to cases in which the country where the security was issued could not be identified.

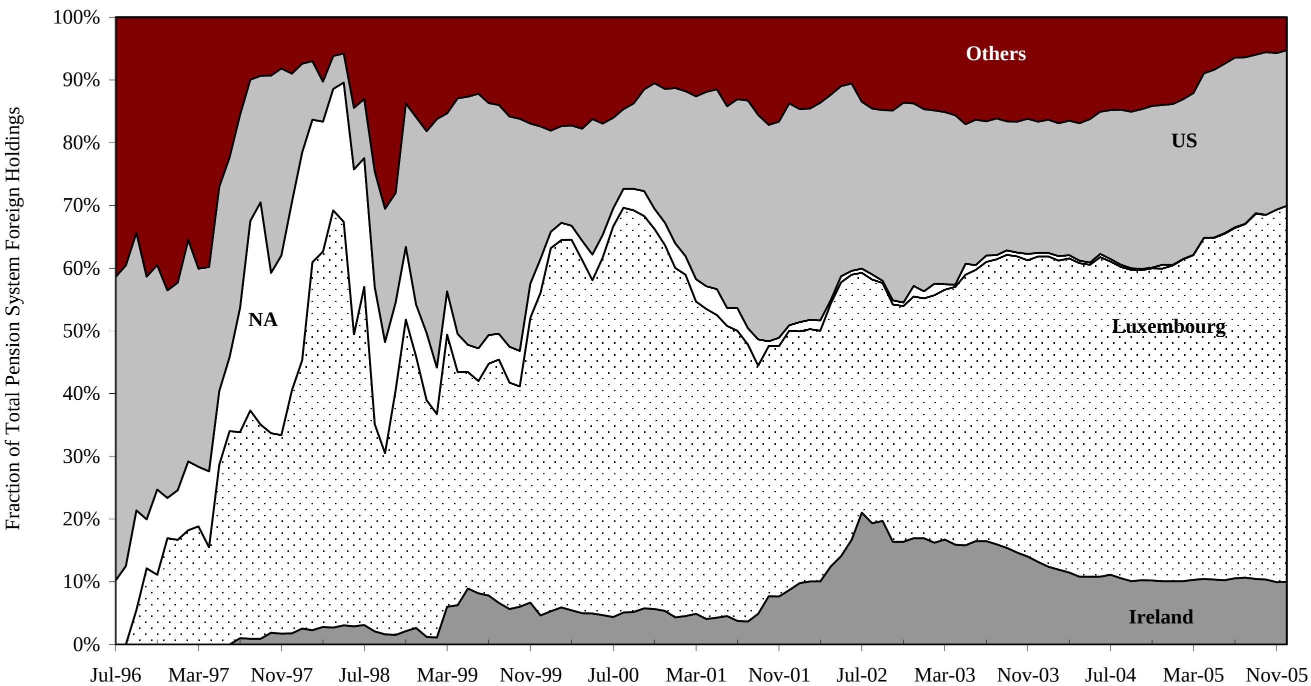


Figure 13
Allocation of PFA Holdings by Asset Class

This figure presents the allocation of holdings per asset class across PFAs for Fund C in December 2005. For each asset class, the figure displays the minimum and maximum weights assigned to each asset class by a PFA, and the box represents the range of weights from percentile 25 to percentile 75. The mark in the center of the box represents the median weight across PFAs per asset class.

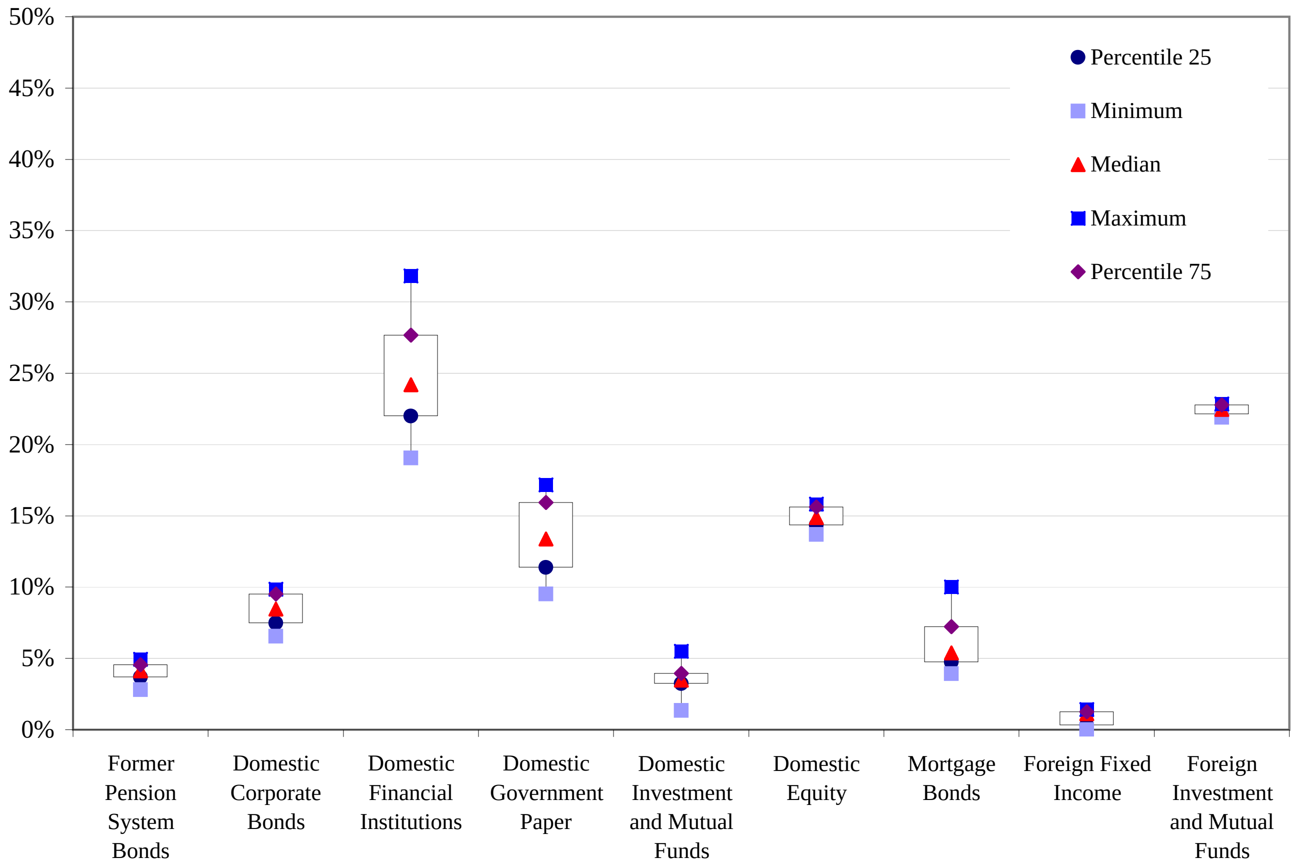
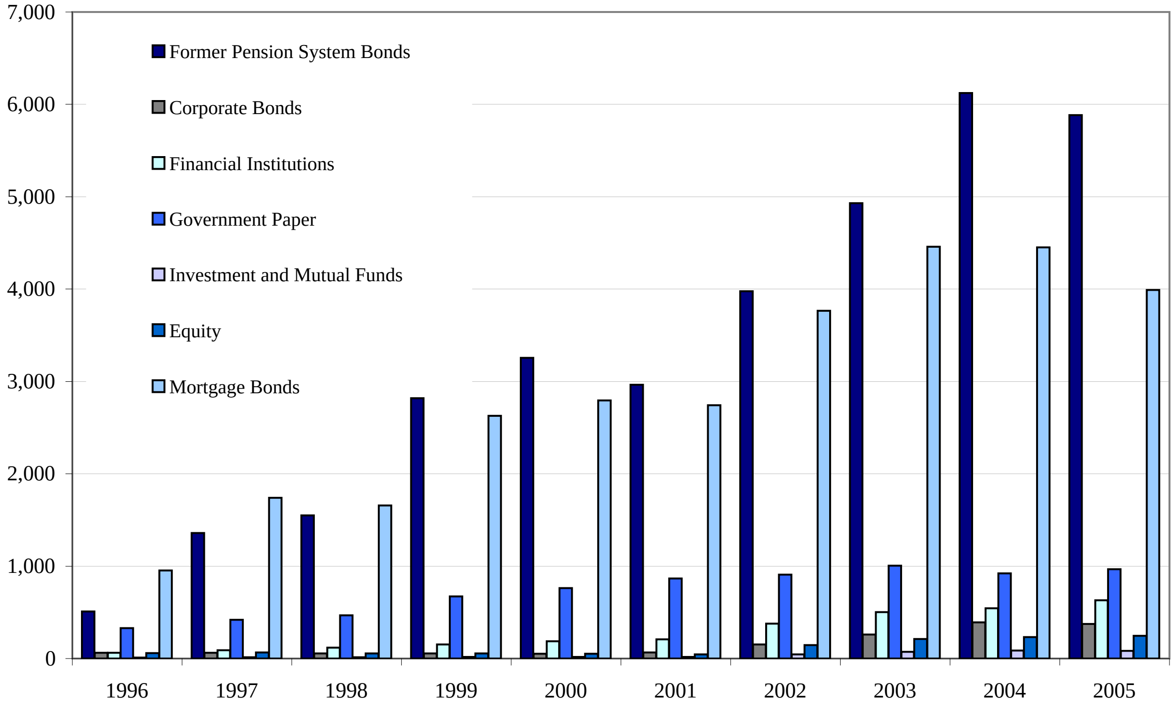


Figure 14
Number of Instruments Held by PFAs

This figure presents the average number of instruments held by PFAs in a given year, per asset class. Since the data has a monthly frequency, we computed the average number of instruments per month and PFA, averaged per year and PFA, and then calculated the median across PFAs for each year. Panel A presents all assets, Panel B presents domestic assets excluding Former Pension System Bonds and Mortgage Bonds, and Panel C presents foreign assets.

Panel A. Median Across PFAs of the Number of Instruments Held - Domestic Assets



Panel B. Median Across PFAs of the Number of Instruments Held - Foreign Assets

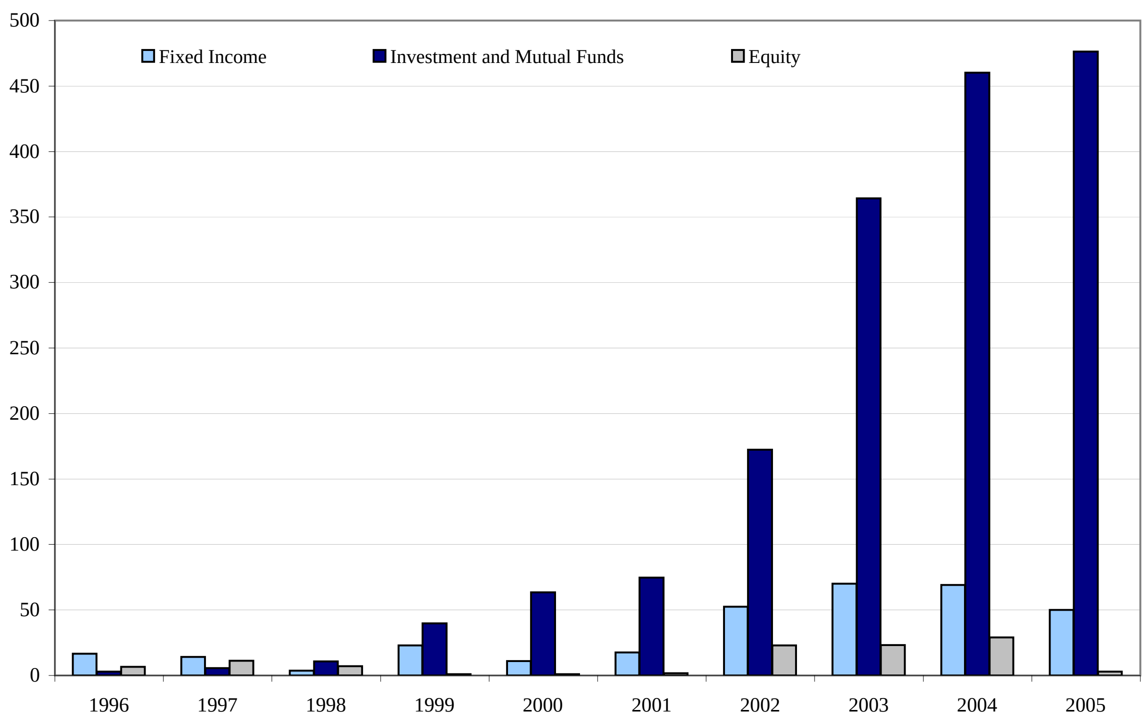
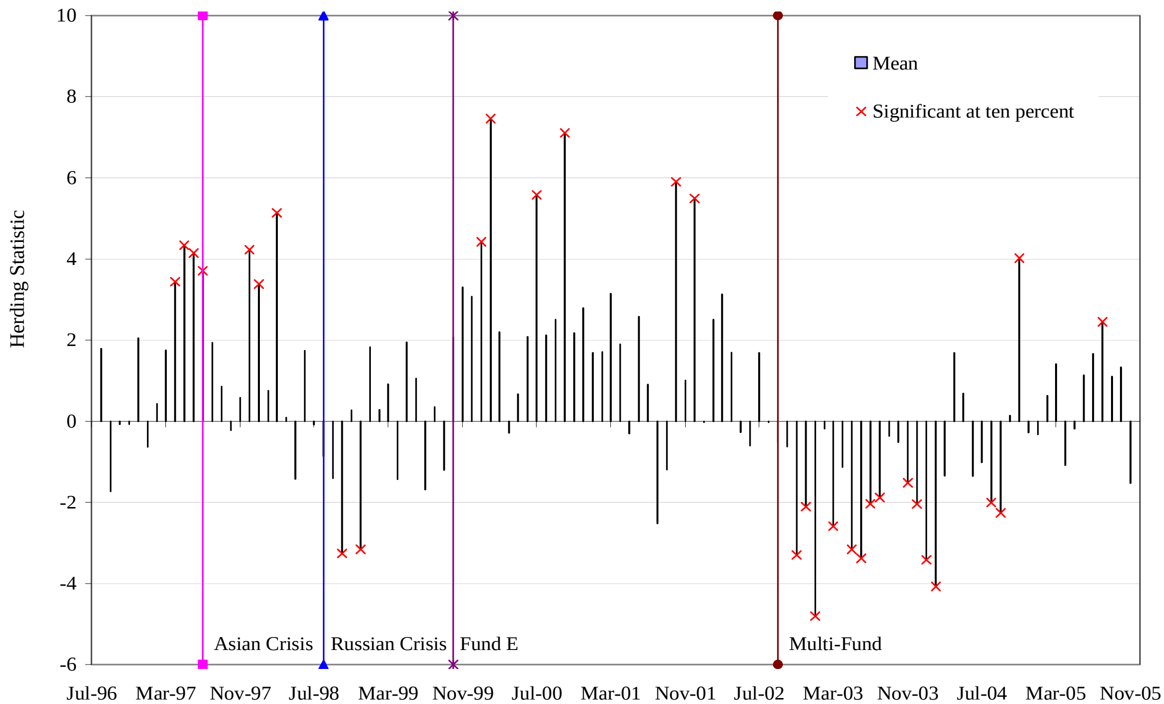


Figure 15
Evolution of Contemporaneous Herding Statistic

This figure presents the evolution of the average Lakonishok et al. (1992) herding statistic during the entire sample period (July 1996 to December 2005). The herding statistic is calculated using the asset-specific probability of buying an asset at a moment in time. Panel A and B present the evolution of the herding statistic for Domestic Equity and Domestic Corporate Bonds, respectively. The averages that are significant at the ten-percent level, according to the two-tailed t-test, are marked on the figure. Significant events that occurred during this period of time are also highlighted: the Asian crisis (July 1997), the Russian crisis (August 1998), the introduction of Fund E and the widening of the minimum return band (October 1999), and the establishment of the multi-fund regime (September 2002). Numbers represent percentages (results are multiplied by 100).

Panel A. Evolution of Herding Statistic - Domestic Equity (1996 - 2005)



Panel B. Evolution of Herding Statistic - Domestic Corporate Bonds (1996 - 2005)

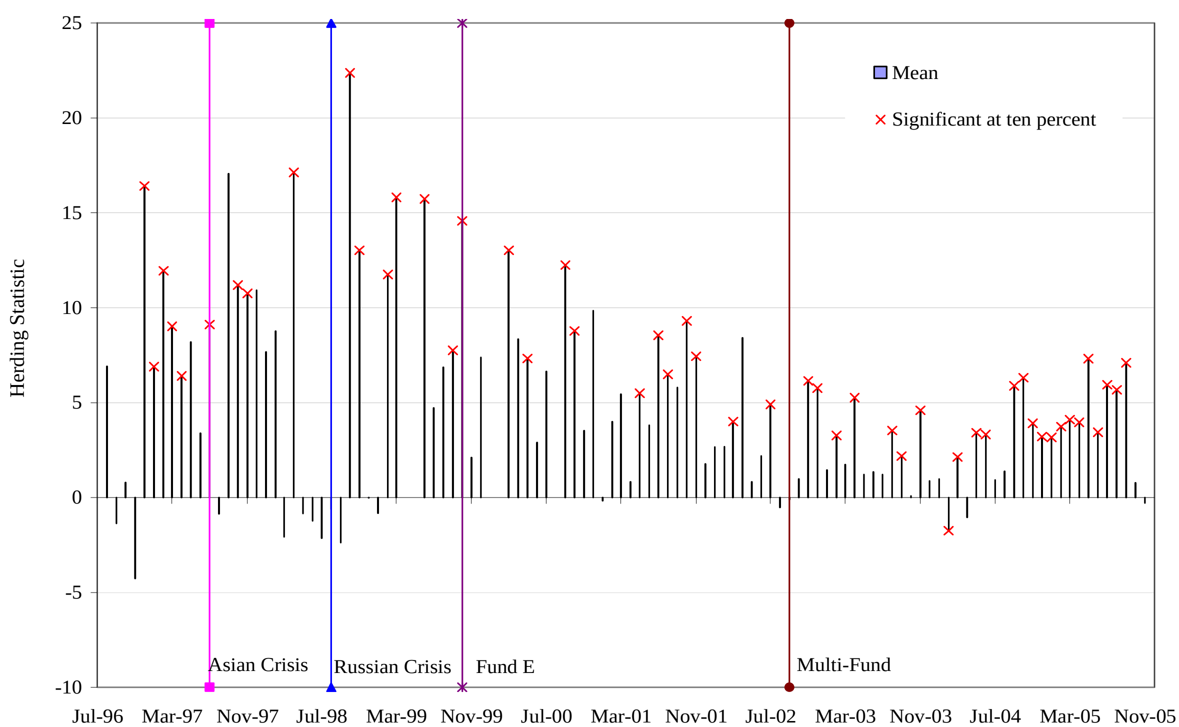
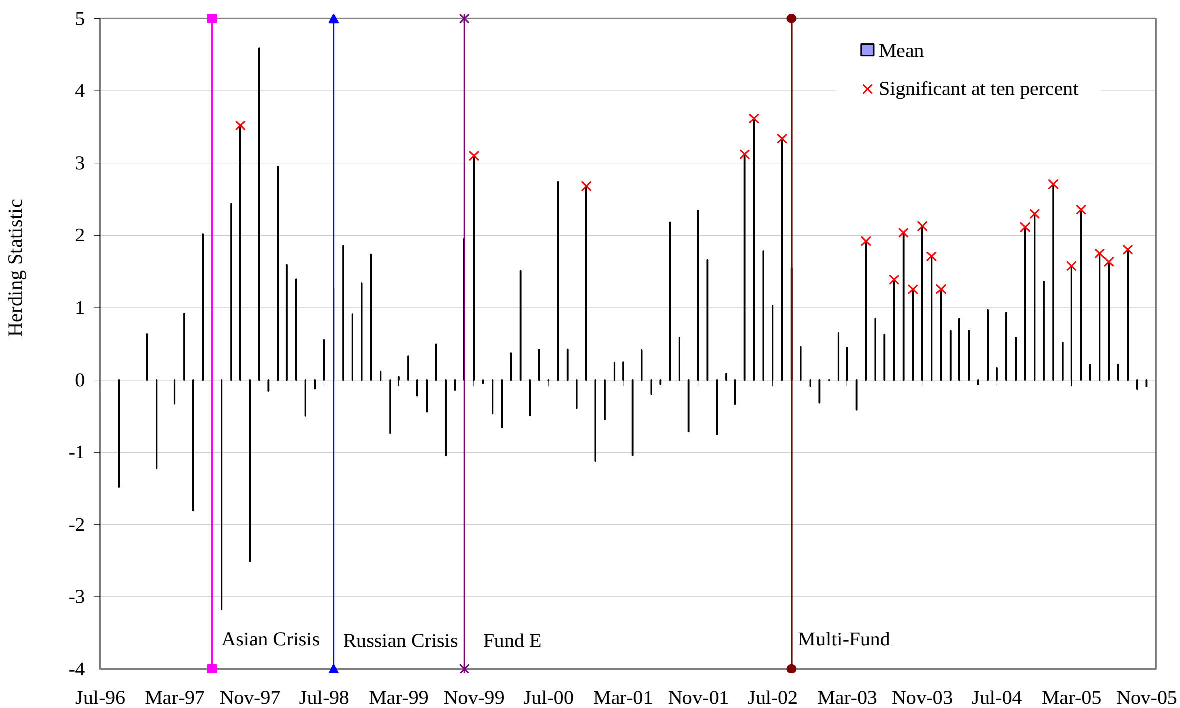


Figure 16
Evolution of Contemporaneous Herding Statistic

This figure presents the evolution of the average Lakonishok et al. (1992) herding statistic during the entire sample period (July 1996 to December 2005). The herding statistic is calculated using the asset-specific probability of buying an asset at a moment in time. Panel A and B present the evolution of the herding statistic for Foreign Investment and Mutual Funds and Domestic Government Paper, respectively. The averages that are significant at the ten-percent level, according to the two-tailed t-test, are marked on the figure. Significant events that occurred during this period of time are also highlighted: the Asian crisis (July 1997), the Russian crisis (August 1998), the introduction of Fund E and the widening of the minimum return band (October 1999), and the establishment of the multi-fund regime (September 2002). Numbers represent percentages (results are multiplied by 100).

Panel A. Evolution of Contemporaneous Herding Statistic - Foreign Investment and Mutual Funds (1996 - 2005)



Panel B. Evolution of Contemporaneous Herding Statistic - Domestic Government Paper (1996 - 2005)

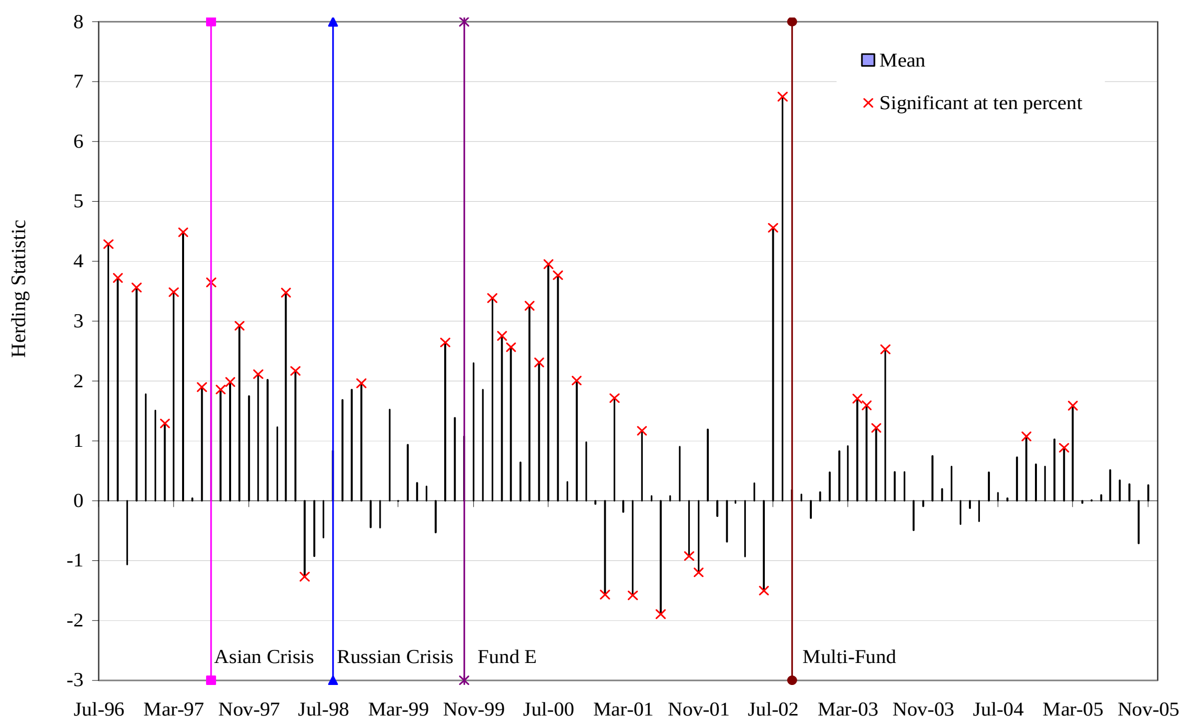
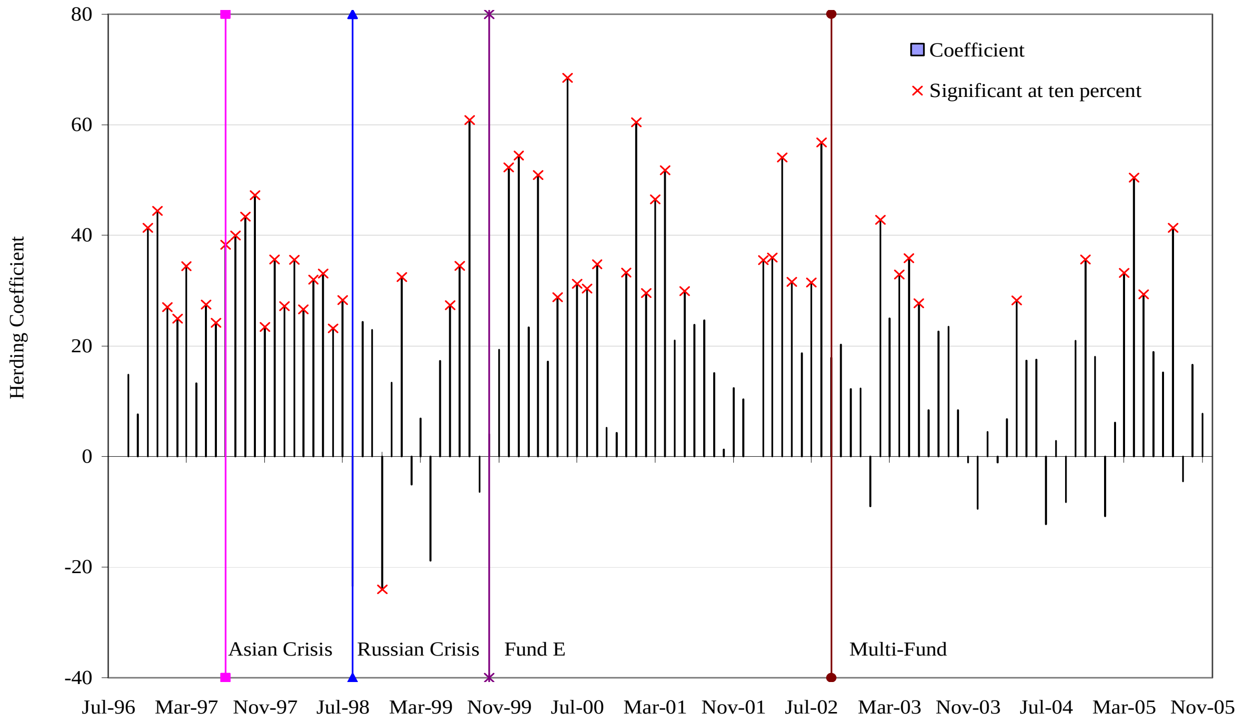


Figure 17
Evolution of Dynamic Herding Coefficients

This figure presents the evolution of the coefficient of the Sias (2004) herding regressions, that is, the regression of the probability of buying an asset at a moment in time on the lagged probability of buying an asset. Panel A and B present the evolution of the coefficients for Domestic Equity and Foreign Investment and Mutual Funds, respectively. The coefficients that are significant at the ten-percent level, according to the two-tailed t-test, are marked on the figure. Significant events that occurred during this period of time are also highlighted: the Asian crisis (July 1997), the Russian crisis (August 1998), the introduction of Fund E and the widening of the minimum return band (October 1999), and the establishment of the multi-fund regime (September 2002). Numbers represent percentages (results are multiplied by 100).

Panel A. Evolution of Dynamic Herding Coefficients - Domestic Equity (1996 - 2005)



Panel B. Evolution of Dynamic Herding Coefficients - Foreign Investment and Mutual Funds (1996 - 2005)

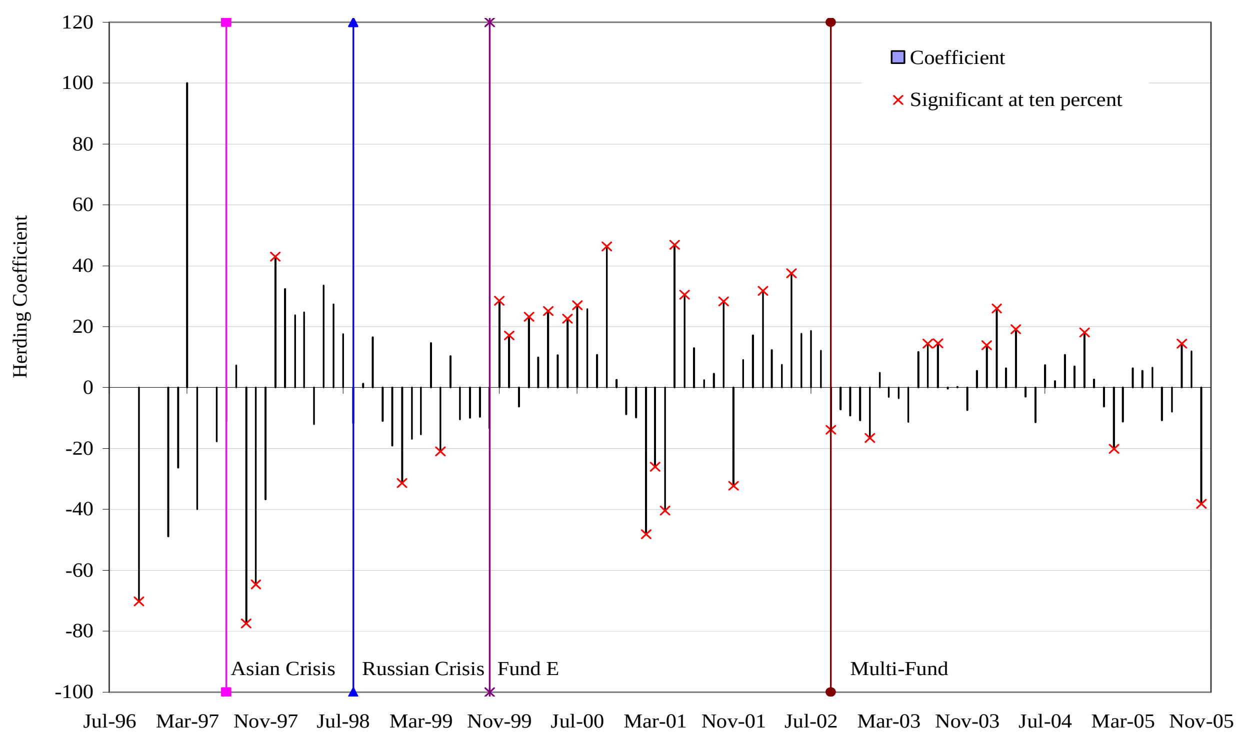


Figure 18
Evolution of Turnover Fixed Effects

This figure presents the evolution of the coefficients obtained from the regression of the Grinblatt et al. (1995) turnover statistic at the PFA-time-fundtype level on PFA, time, and fund type fixed effects. This figure considers the entire sample period (July 1996 to December 2005). The zero-mean time fixed effects are presented in the figure. Coefficients that are statistically significant at the ten-percent level are marked on the figure. T-tests are two-tailed. Significant events that occurred during this period of time are also highlighted on the figure: the Asian crisis (July 1997), the Russian crisis (August 1998), the introduction of Fund E and the widening of the minimum return band (October 1999), and the establishment of the multi-fund regime (September 2002). Numbers represent percentages (results are multiplied by 100).

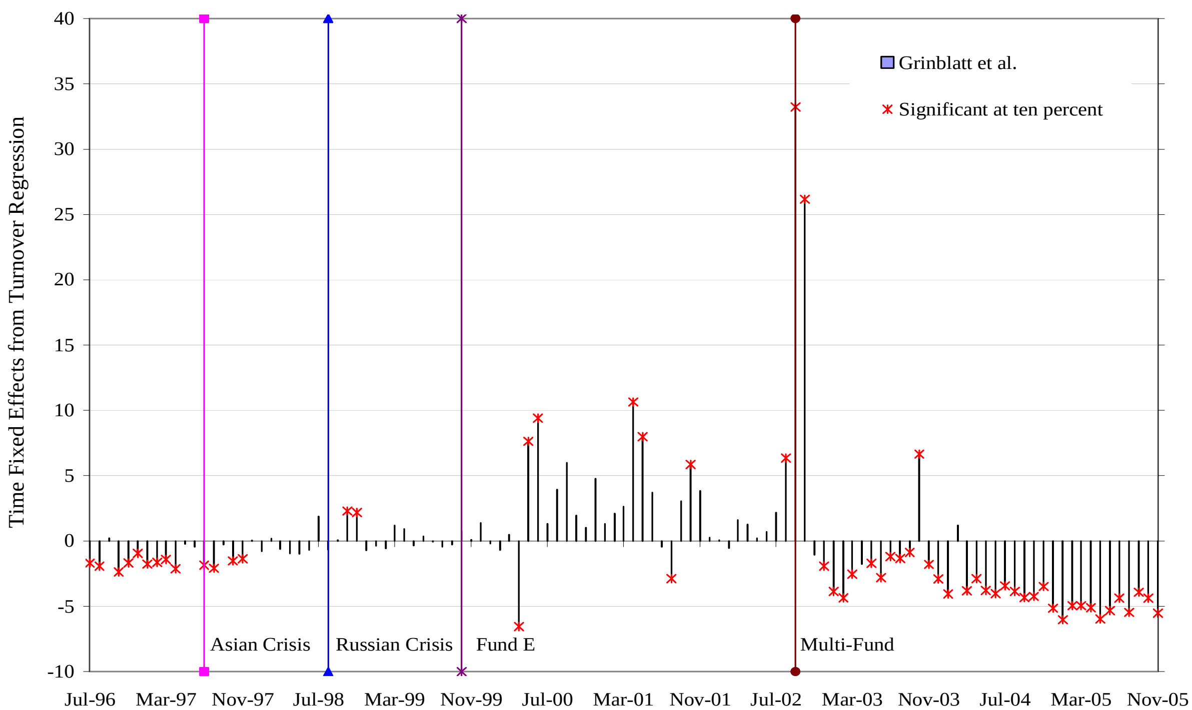


Figure 19
Evolution of Turnover Fixed Effects (Pre Multi-Fund Regime)

This figure presents the evolution of the coefficients obtained from the regression of the Grinblatt et al. (1995) turnover statistic at the PFA-time-fundtype level on PFA, time, and fund type fixed effects. This figure only considers the period previous to the multi-fund regime (July 1996 to August 2002). The zero-mean time fixed effects are presented in the figure. Coefficients that are statistically significant at the ten-percent level are marked on the figure. T-tests are two-tailed. Significant events that occurred during this period of time are also highlighted on the figure: the Asian crisis (July 1997), the Russian crisis (August 1998), and the introduction of Fund E and the widening of the minimum return band (October 1999). Numbers represent percentages (results are multiplied by 100).

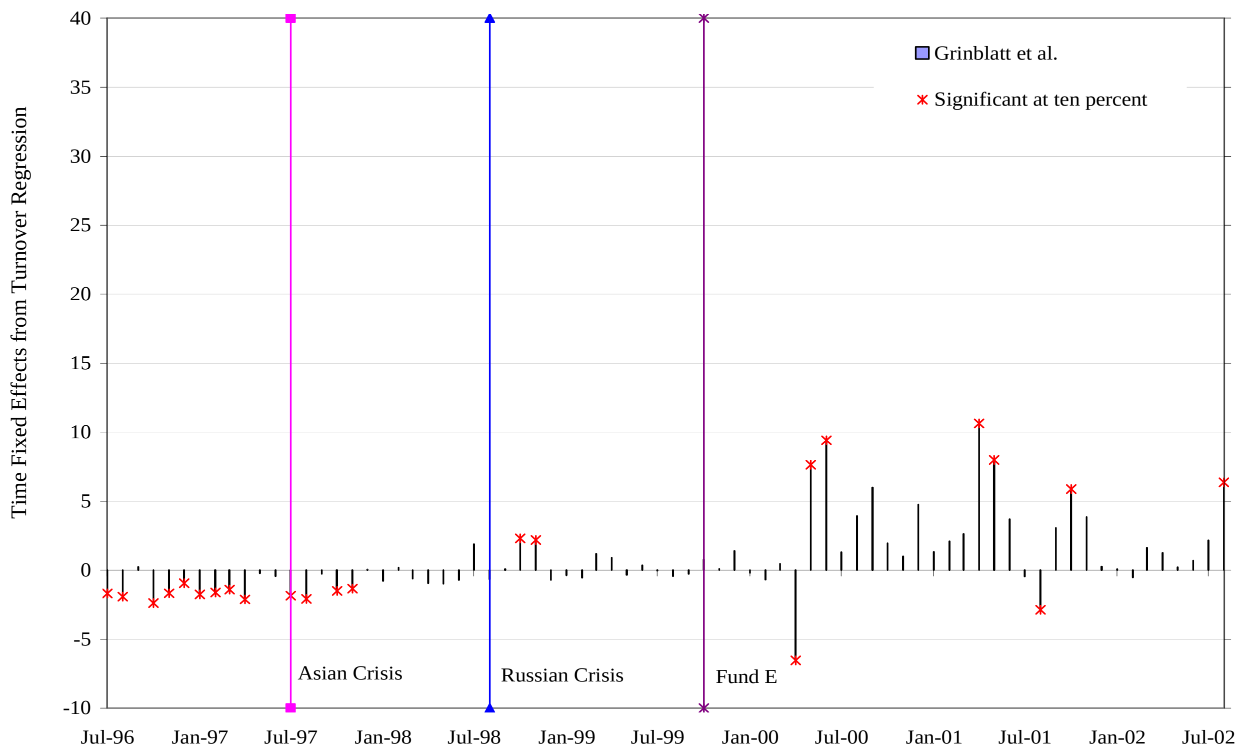
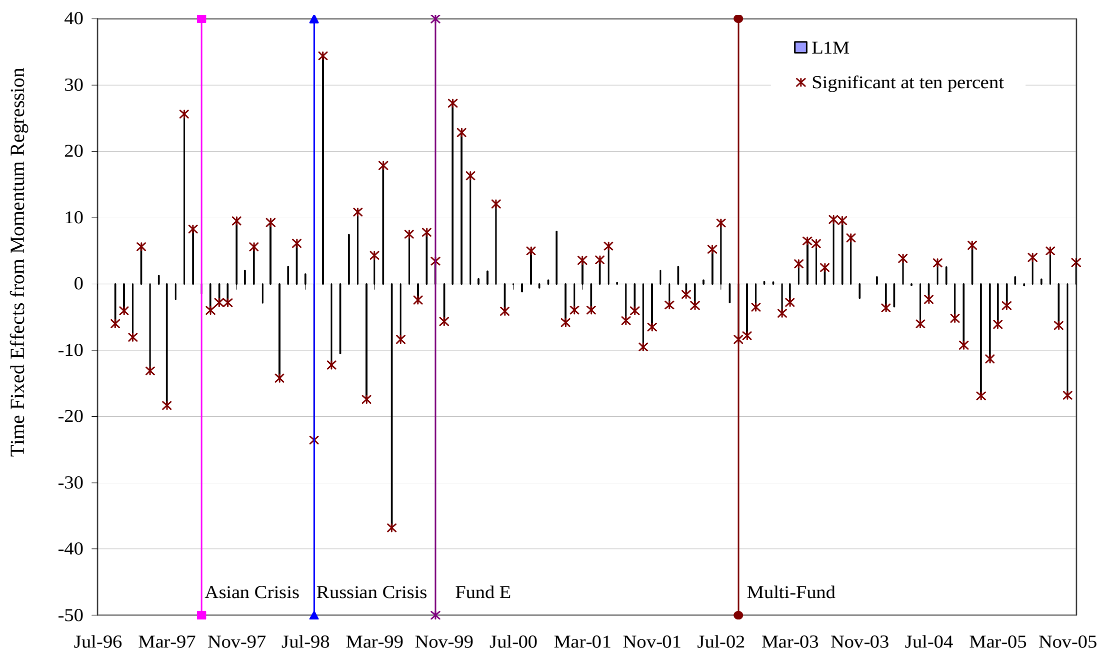


Figure 20
Time Fixed Effects of Momentum Statistics

This figure presents the time fixed effects obtained from the regression of the Grinblatt et al. (1995) momentum statistics on time and PFA fixed effects. Panel A presents the Contemporaneous Momentum Statistic L1M and Panel B presents the Lagged Momentum Statistic L0M. Coefficients that are statistically significant at the ten-percent level are marked on the figure. T-tests are one-tailed. Numbers represent percentages (coefficients are multiplied by 10,000 - weights and returns are in percentages). Significant events that occurred during this period of time are also highlighted on the figure: the Asian crisis (July 1997), the Russian crisis (August 1998), the introduction of Fund E and the widening of the minimum return band (October 1999), and the establishment of the multi-fund regime (September 2002).

Panel A. L1M Time Fixed Effects (1996 - 2005)



Panel B. L0M Time Fixed Effects (1996 - 2005)

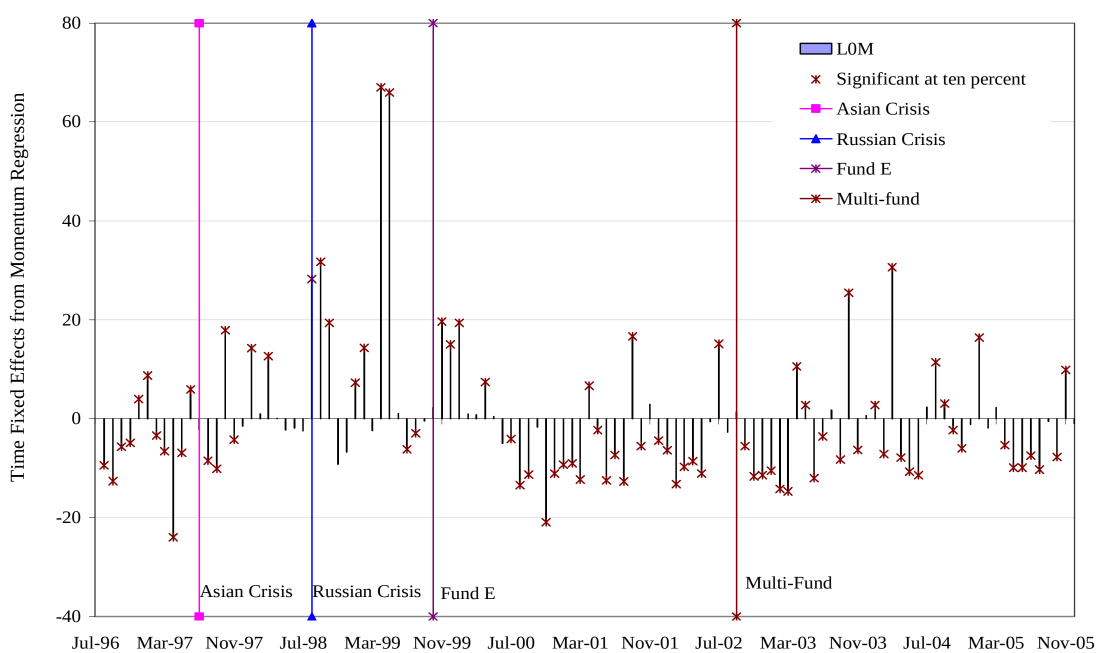
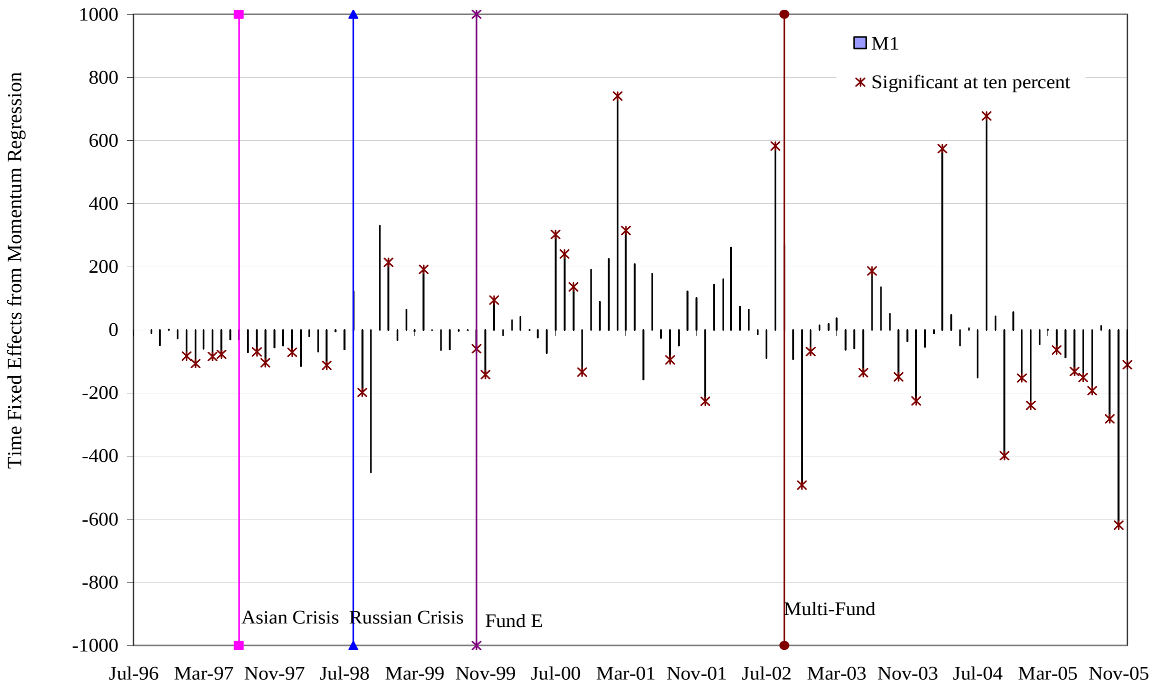


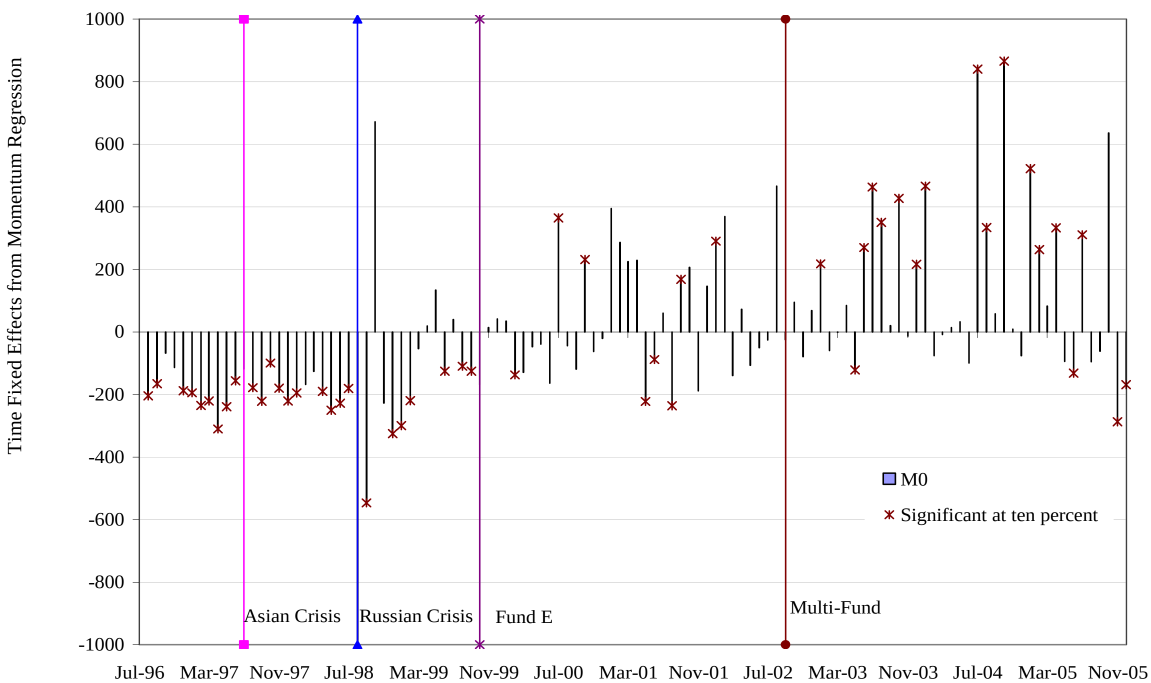
Figure 21
Time Fixed Effects of Momentum Statistics

This figure presents the time fixed effects obtained from the regression of the Kaminsky et al. (2004) momentum statistics on time and PFA fixed effects. Panel A presents the Contemporaneous Momentum Statistic M1 and Panel B presents the Lagged Momentum Statistic M0. Coefficients that are statistically significant at the ten-percent level are marked on the figure. T-tests are one-tailed. Numbers represent percentages (coefficients are multiplied by 100). Significant events that occurred during this period of time are also highlighted on the chart: the Asian crisis (July 1997), the Russian crisis (August 1998), the introduction of Fund E and the widening of the minimum return band (October 1999), and the establishment of the multi-fund regime (September 2002).

Panel A. M1 Time Fixed Effects (1996 - 2005)



Panel B. M0 Time Fixed Effects (1996 - 2005)



Appendix Table 1
Contemporaneous Herding Statistics

This table presents the average Lakonishok et al. (1992) herding statistic calculated over all assets and by asset class. The herding statistic is calculated using the overall portfolio probability of buying an asset at any point in time. Column (1) presents the results considering all assets, column (2) considers assets traded by more than one PFA, and column (3) considers assets traded by more than half of the PFAs in operation at any point in time. T-tests are two-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. The standard error from the significance t-test is presented in parenthesis. Numbers represent percentages (results are multiplied by 100). The dashes in column (3) indicate asset classes that are not traded by more than half of PFAs in operation.

	Herding Statistic		
	All Assets	Assets Traded by More Than One PFA	Assets Traded by More Than Half of PFAs
	(1)	(2)	(3)
All Asset Classes	4.32**	8.28**	10.48**
	(0.02)	(0.05)	(0.11)
Domestic Assets			
Former Pension System Bonds	0.69**	-13.13**	4.99**
	(0.03)	(0.10)	(0.59)
Corporate Bonds	4.52**	9.40**	8.97**
	(0.26)	(0.69)	(0.58)
Financial Institutions	5.81**	12.48**	10.59**
	(0.07)	(0.24)	(1.03)
Government Papers	2.76**	2.61**	5.91**
	(0.08)	(0.19)	(0.57)
Investment and Mutual Funds	7.18**	18.41**	5.01**
	(0.72)	(1.83)	(0.74)
Equity	4.98**	5.57**	4.45**
	(0.21)	(0.29)	(0.29)
Mortgage Bonds	7.63**	15.12**	14.75**
	(0.04)	(0.05)	(0.13)
Foreign Assets			
Fixed Income	3.16**	6.16**	26.50**
	(0.22)	(1.13)	(4.87)
Investment and Mutual Funds	6.24**	8.32**	4.06**
	(0.15)	(0.27)	(0.37)
Equity	4.30**	4.8*	-
	(0.27)	(2.58)	-

Appendix Table 2
Momentum Statistics on Asset Class Fixed Effects

This table presents the results of the regressions of momentum statistics at the PFA-time level on PFA and time fixed effects. The table displays the constant corresponding to the regression of each momentum statistic on the fixed effects. We also present the proportion of PFAs that are momentum or contrarian traders at a ten-percent significance level, according to the t-test of the sum of the constant and the coefficient corresponding to each PFA. T-tests are one-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Standard errors are presented in parentheses. The coefficients and standard errors are multiplied by 100 in the case of the Kaminsky et al. measure (returns are in percentages) and by 10,000 in the case of the other measures (weights and returns are in percentages).

		Lagged Momentum Statistics			Contemporaneous Momentum Statistics		
		L1M Grinblatt et al.	LM1 Ferson and Khang	M1 Kaminsky et al.	L0M Grinblatt et al.	LM0 Ferson and Khang	M0 Kaminsky et al.
		(1)	(2)	(3)	(4)	(5)	(6)
All Asset Classes	Constant	3.99**	4.72**	76.42**	23.1**	-2.62**	286.94**
	Standard Error	(0.94)	(0.94)	(21.72)	(0.83)	(0.95)	(44.57)
	% Momentum Traders	50.00%	79.17%	58.33%	100.00%	4.17%	91.67%
	% Contrarian Traders	0.00%	0.00%	0.00%	0.00%	45.83%	0.00%
Domestic Assets							
Former Pension System Bonds	Constant	-0.00	-0.00	34.53	0.09**	-0.02	45.26**
	Standard Error	(0.02)	(0.02)	(22.83)	(0.02)	(0.01)	(22.87)
	% Momentum Traders	17.39%	21.74%	17.39%	78.26%	21.74%	30.43%
	% Contrarian Traders	13.04%	17.39%	0.00%	0.00%	21.74%	0.00%
Corporate Bonds	Constant	0.04	0.21**	0.99	0.88**	-0.03	0.40
	Standard Error	(0.12)	(0.10)	(1.33)	(0.06)	(0.04)	(1.52)
	% Momentum Traders	4.17%	29.17%	16.67%	87.50%	4.17%	8.33%
	% Contrarian Traders	20.83%	0.00%	0.00%	4.17%	16.67%	8.33%
Financial Institutions	Constant	0.09	0.12	4.48**	0.49**	0.14**	5.60**
	Standard Error	(0.08)	(0.07)	(1.24)	(0.07)	(0.07)	(1.24)
	% Momentum Traders	29.17%	33.33%	50.00%	62.50%	37.50%	50.00%
	% Contrarian Traders	20.83%	20.83%	4.17%	4.17%	25.00%	12.50%
Government Paper	Constant	0.49	0.87**	15.35**	4.77**	0.94**	29.39**
	Standard Error	(0.40)	(0.40)	(4.35)	(0.35)	(0.29)	(6.022)
	% Momentum Traders	16.67%	29.17%	54.17%	100.00%	54.17%	75.00%
	% Contrarian Traders	20.83%	0.00%	4.17%	0.00%	8.33%	4.17%
Investment and Mutual Funds	Constant	-0.11	-0.21*	-0.99	0.33**	0.00	-0.07
	Standard Error	(0.12)	(0.12)	(1.08)	(0.02)	(0.01)	(0.22)
	% Momentum Traders	20.83%	4.17%	0.00%	100.00%	4.17%	12.50%
	% Contrarian Traders	4.17%	29.17%	4.17%	0.00%	0.00%	4.17%
Equity	Constant	3.00**	2.79**	26.32**	9.33**	-4.92**	-9.98**
	Standard Error	(0.76)	(0.76)	(2.93)	(0.69)	(0.84)	(3.62)
	% Momentum Traders	50.00%	41.67%	87.50%	87.50%	0.00%	0.00%
	% Contrarian Traders	0.00%	0.00%	0.00%	0.00%	87.50%	41.67%
Mortgage Bonds	Constant	-0.27**	0.05	-17.42	1.41**	0.36**	203.24**
	Standard Error	(0.10)	(0.10)	(14.13)	(0.09)	(0.10)	(23.14)
	% Momentum Traders	4.17%	12.50%	0.00%	91.67%	66.67%	100.00%
	% Contrarian Traders	54.17%	8.33%	33.33%	0.00%	4.17%	0.00%
Foreign Assets							
Fixed Income	Constant	0.10	0.14	1.39*	0.49**	-0.01	1.49*
	Standard Error	(0.12)	(0.12)	(0.76)	(0.16)	(0.16)	(0.90)
	% Momentum Traders	8.33%	16.67%	25.00%	66.67%	16.67%	33.33%
	% Contrarian Traders	0.00%	0.00%	0.00%	0.00%	25.00%	8.33%
Investment and Mutual Funds	Constant	0.76**	0.70**	13.41**	3.67**	1.00**	15.65**
	Standard Error	(0.25)	(0.25)	(2.74)	(0.21)	(0.23)	(3.15)
	% Momentum Traders	70.00%	70.00%	70.00%	90.00%	80.00%	80.00%
	% Contrarian Traders	5.00%	5.00%	0.00%	0.00%	5.00%	10.00%
Equity	Constant	0.03	0.03	1.47	0.19**	0.09**	0.85
	Standard Error	(0.04)	(0.05)	(4.22)	(0.05)	(0.04)	(4.16)
	% Momentum Traders	10.00%	10.00%	40.00%	70.00%	40.00%	10.00%
	% Contrarian Traders	10.00%	10.00%	20.00%	0.00%	0.00%	10.00%

Appendix Table 3
Momentum Statistics (Using Weights With Lagged Price)

This table presents the average across PFAs of the Grinblatt et al. (1995) momentum statistic and the percentage of PFAs that are momentum or contrarian traders at a ten-percent significance level. The statistic is calculated using weights with the lagged price. T-tests are one-tailed. One asterisk indicates statistical significance at the ten-percent level and two asterisks indicate statistical significance at the five-percent level. Standard errors are presented in parentheses. The averages and standard errors are multiplied by 100 in the case of the Kaminsky et al. measure (returns are in percentages) and by 10,000 in the case of the other measures (weights and returns are in percentages). In addition, t-tests are computed for each PFA and momentum statistic in order to calculate the percentage of PFAs that are momentum or contrarian traders at a ten-percent significance level.

		Lagged Momentum Statistic	Contemporaneous Momentum Statistic
		L1M Grinblatt et al.	L0M Grinblatt et al.
		(1)	(2)
All Asset Classes	Average Statistic	9.03**	-57.89**
	Standard Error	(0.01)	(0.13)
	% Momentum Traders	0.58%	0.04%
	% Contrarian Traders	0.00%	0.04%
Domestic Assets			
Former Pension System Bonds	Average Statistic	0.12**	0.11**
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.48%	0.57%
	% Contrarian Traders	0.04%	0.00%
Corporate Bonds	Average Statistic	0.18	-0.06
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.04%	0.04%
	% Contrarian Traders	0.00%	0.21%
Financial Institutions	Average Statistic	0.16**	0.28**
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.50%	0.58%
	% Contrarian Traders	0.08%	0.17%
Government Paper	Average Statistic	0.41	0.70**
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.13%	0.25%
	% Contrarian Traders	0.17%	0.08%
Investment and Mutual Funds	Average Statistic	-0.22**	0.04**
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.17%	0.38%
	% Contrarian Traders	0.00%	0.00%
Equity	Average Statistic	7.79**	-59.3**
	Standard Error	(0.01)	(0.13)
	% Momentum Traders	0.42%	0.04%
	% Contrarian Traders	0.00%	0.08%
Mortgage Bonds	Average Statistic	-0.17**	0.40**
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.13%	0.50%
	% Contrarian Traders	0.38%	0.00%
Foreign Assets			
Fixed Income	Average Statistic	0.17**	0.03
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.25%	0.25%
	% Contrarian Traders	0.00%	0.17%
Investment and Mutual Funds	Average Statistic	0.85**	0.00
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.55%	0.25%
	% Contrarian Traders	0.05%	0.00%
Equity	Average Statistic	0.04**	0.01
	Standard Error	(0.00)	(0.00)
	% Momentum Traders	0.10%	0.10%
	% Contrarian Traders	0.00%	0.00%