WPS5700

Policy Research Working Paper 5700

Deconstructing Herding

Evidence from Pension Fund Investment Behavior

Claudio Raddatz
Sergio L. Schmukler

The World Bank
Development Research Group
Macroeconomics and Growth Team
June 2011

Policy Research Working Paper 5700

Abstract

Pension funds have been expected to invest in a wide range of securities and provide liquidity to domestic capital markets since they are the most sophisticated investors, with plenty of resources to gather private information and manage portfolios professionally. However, by analyzing unique, monthly asset-level data from the pioneer case of Chile, this paper shows that pension funds tend to herd. This is consistent with pension funds copying each other in their investment strategies as a way to extract information, boost returns, and reduce risk. The authors compute measures of herding across asset classes (equities, government bonds, and private sector bonds) and at different pension fund industry levels. The results show that pension funds herd more in assets for which they have less market information and when risk increases. Moreover, herding is more prevalent across funds that narrowly compete with each other, that is, when comparing funds of the same type across pension fund administrators. There is much less herding within pension fund administrators and across pension fund administrators as a whole. This herding pattern is consistent with incentives for managers to be close to industry benchmarks, which might be driven by both market forces and regulation.

This paper is a product of the Macroeconomics and Growth Team, Development Research Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at sschmukle@worldbank.org.

DECONSTRUCTING HERDING:
EVIDENCE FROM PENSION FUND INVESTMENT BEHAVIOR

Claudio Raddatz and Sergio L. Schmukler *

JEL Classification Codes: G11, G12, G23, G28, O16

Keywords: institutional investors, portfolio allocation, investment pattern, capital market development

* We are indebted to the Chilean Superintendency of Pensions for giving us unique data and support that made this paper possible. For very useful comments, we thank Solange Berstein, Matias Braun, Pablo Castañeda, Eduardo Fajnzylber, David Musto, Gonzalo Reyes, Luis Serven, and participants at presentations held at the LACEA Annual Meetings (Buenos Aires, Argentina), NIPFP-DEA Workshop (Delhi, India), Superintendencia de Pensiones and Universidad Alfonso Ibañez (Santiago, Chile), and World Bank Group (Washington, DC). For excellent research assistance, we are especially grateful to Ana Gazmuri and Mercedes Politi. We also thank Alfonso Astudillo, Leandro Brufman, and Francisco Ceballos, who helped us at different stages of the project. The World Bank Research Department and the Knowledge for Change Program provided generous financial support. The views expressed here do not necessarily represent those of the World Bank. Authors are with the World Bank, Development Economics Research Group. Email addresses: craddatz@worldbank.org and sschmukler@worldbank.org.

1. Introduction

This paper uses a unique and rich micro dataset on pension funds to shed new light on how incentives might affect institutional investors in their portfolio allocation decisions. In particular, we study two aspects discussed in the literature but still relatively unexplored: (i) how institutional investors trade in different types of assets and (ii) what incentives managers at various layers of the financial industry face when implementing their investment strategies. Because of the interest of the literature in herding behavior, we focus on herding statistics. This kind of analysis helps understand more broadly the role of institutional investors on capital market activity and the services they effectively provide as financial intermediaries. Furthermore, it offers new evidence on the importance of several factors often discussed in the literature on the behavior of institutional investors, including information, liquidity, incentives related to organizational aspects of the financial industry, and the regulatory framework in which managers operate.

Institutional investors are interesting to analyze not only because they have become very large, but also because detailed asset-level portfolios over time (unavailable at the household or retail-investor level) are sometimes accessible. In particular, institutional investors are increasingly relevant for both asset management and the development of financial systems. In fact, institutional investors are likely to be among the most important conduits of private and public savings, intermediating funds and supplying capital for firms and countries to grow. As institutional investors became prevalent, research flourished trying to understand how they invest. Many papers in the literature focus on equity mutual funds, for which portfolio data are mostly publicly available, and study their investment patterns (Grinblatt et al., 1995; Wermers, 1999; and Kacperczyk et al., 2005). Others analyze general data on institutional investors (Sias and Starks, 1997; Nofsinger and Sias, 1999; Grinblatt and Keloharju, 2000; Sias, 2004; and Choi and Sias, 2009).

In this paper, we exploit new data and analyze the investment behavior of pension funds, for which relatively little is known although they have played a crucial role across countries. The few studies available on pension fund investment behavior are very informative, but they only use part of the data available on pension funds in a given country. They typically use quarterly data for a subsample of pension funds and focus exclusively on equity holdings. Lakonishok et al. (1992), Badrinath and Wahal (2002), and Ferson and Khang (2002) analyze US data, while Blake et al. (2002) and Voronkova and Bohl (2005) analyze data from the UK and Poland, respectively. The limited scope of the data and the emphasis on equity holdings present important shortcomings because most pension funds worldwide invest a large fraction of their portfolios in bonds and other types of assets, and their trading patterns might differ significantly across asset classes.

We use data from Chile, which was the first country to embrace the new mandatory, privately managed, defined-contribution (DC) pension fund model, by replacing the public, defined-benefit (DB) pension system with a DC one in May 1981. Many developed and developing countries have followed suit and reformed their pension regimes, establishing very similar pension funds.[1] For example, the UK moved toward a multi-pillar pension system in 1986. Sweden modified in 1994 the pension system from a pay-as-you-go DB to a second-pillar system that includes a voluntary DC system. In the US, proposals to reform the social security system were also recurrently considered. Following Chile's example, many developing countries adopted similar reforms, including Argentina, Bolivia, Colombia, Costa Rica, the Dominican

[1] These changes reached even the corporate sector, entailing a shift away from defined-benefit schemes toward defined-contribution schemes to transfer risk from corporations to employees.

Republic, El Salvador, Hungary, Kazakhstan, Lithuania, Mexico, Peru, Slovakia, Poland, and Uruguay.

The data we assemble contain the detailed portfolios of the universe of Chilean pension funds in all types of securities and asset classes at a monthly frequency for ten years, 1996 to 2005. We also compile the monthly returns of each instrument included in these portfolios. The dataset contains 3,869,290 observations, with information on the holdings and returns of 24,322 different securities for up to 57 pension funds. We then compute different estimates of herding, which are associated with funds buying/selling the same assets simultaneously.

This new dataset allows us to shed light on a series of questions regarding different aspects of pension fund investment strategies and overall behavior. In particular, do pension funds herd, buying/selling the same assets simultaneously? Is their herding pattern different across asset classes with varying liquidity and information? Does their herding behavior vary at different levels of the pension fund organization structure? What does their behavior tell about the incentives that managers face to compete with each other? Does herding change with purchases in primary and secondary markets? Does it differ on the buying and selling sides? Is trading activity associated with variations in returns? Understanding herding is important because this behavior can contribute to market volatility. Moreover, it means that managers are not generating independent assessments in the markets and might not be providing different services to pensioners.

In addressing these questions, we investigate at least three important aspects of herding discussed in the literature. First, traders might copy other traders in the process of extracting private information (Shiller and Pound, 1989; Sharfstein and Stein, 1990; Banerjee, 1992; and Bikhchandani et al., 1992). Since some assets are more obscure than others, the degree of herding is expected to decrease with the transparency of the assets for a given level of risk.[2] In other words, securities for which information is widely available and that entail less risk are less likely to induce herding patterns. We thus exploit our dataset to analyze herding by asset type by the same institutional investors. In particular, we calculate herding in corporate bonds, financial institutions bonds, government bonds, mortgage bonds, and equity.

Second, herding might also be explained by managers following similar trading strategies like momentum (Froot et al., 1992 and Gompers and Metrick, 2001). Momentum trading, defined as the purchasing (selling) of assets whose returns are positive (negative), is a popular investment strategy and has been often found in developed and developing countries. Its presence among US institutional investors (primarily mutual funds) has been widely documented in the literature.[3] Our data on returns allows us to test whether, to the extent that there is herding, it is driven by momentum strategies.

Third, managers might herd as a way to reduce risk. While traditional theories of asset allocation focus on the problem of an isolated investor whose goal is to maximize wealth or consumption at some point in time, several papers study the incentives schemes that arise in the context of financial intermediation. In particular, the conflicts of interest between fund managers and the underlying investors can affect manager risk-taking behavior (Sharfstein and Stein, 1990; Shleifer and Vishny, 1990; Chevalier and Ellison, 1999; Graham, 1999; Stein, 2003, 2005;

[2] Although theoretical models of herding behavior do not focus on the characteristic of the assets as a determinant of herding, they typically imply a relation with opacity. For instance, in Sharfstein and Stein (1990), herding can only occur when there are "systematically unpredictable factors affecting the future state that nobody can know anything about," that is, under the presence of an unobservable common component to prediction errors. This type of situation is more likely in less transparent assets. In transparent assets, most of the prediction errors should be idiosyncratic. Similarly, in the model of Banerjee (1992), the probability that no agent chooses the right investment option because of herding is declining in the probability that an agent receives a signal about the state of nature, and in the probability that the signal is true. In the context of asset selection, these probabilities are likely to be lower for more opaque assets.

[3] See, for example, Grinblatt et al. (1995), Nofsinger and Sias (1999), Grinblatt and Keloharju (2000), Kaminsky et al. (2004), Sias (2004, 2007), and Greenwood and Nagel (2009).

Kapur and Timmermann, 2005; and Bolton et al., 2006). The underlying investors, the regulator, and the asset management companies monitor managers on a short-run basis to reduce principal-agent problems, generating incentives for managers to be averse to investments that (though potentially profitable) are different from those held by their competitors. Namely, deviating from the pack might entail reputational costs or regulatory penalties since the principal cannot evaluate whether the agent deviated for good reasons. Herding behavior is thus a natural response of managers to avoid penalties. The data we assemble allow us to study herding at different levels of the pension fund industry. In particular, we study herding among pension fund administrators (PFAs), individual pension funds across the entire industry, individual pension funds within PFAs, and similar types of pension funds across PFAs. We expect herding to increase for fund managers of similar types of pension funds, as comparisons are easier to make and competition intensifies.

The main results from this paper can be summarized as follows. First, pension funds tend to herd on their investment decisions, that is, they buy/sell the same assets at the same time. Second, herding varies substantially across asset classes. In particular, herding is more pronounced in corporate bonds and financial institutions bonds (which are similar to corporate bonds), while there is less herding in equity and mortgage bonds. Relative to corporate bonds, equity is better known by investors since few, large companies are the ones that tend to dominate trading activity. Moreover, equity tends to be traded frequently in secondary markets, sending continuous price signals to investors. Instead, similarly to the US, Chilean corporate bonds trade infrequently and part of their trading occurs over the counter.[4] Mortgage bonds are safer than corporate bonds since they are backed by real estate. Furthermore, the asset class in which the

[4] For the relationship between size, trading activity, and opacity, see Bessembinder and Maxwell (2008) and Livingston et al. (2007).

least herding occurs is government bonds, which are issued by a well-known government that has followed transparent and sound macroeconomic policies and are in turn the assets perceived to bear the lowest risk. In other words, pension funds tend to herd more in the asset classes that are more opaque. The results hold across different levels of the pension fund industry. This result is consistent with pension funds trying to copy each other in their portfolio decisions, especially for the assets for which they can derive less information from the markets. Third, herding is the most intense when comparing funds of the same type across PFAs. That is, herding peaks as funds narrowly compete with each other across PFAs to retain pensioners and/or avoid market or regulatory punishment. PFAs as a whole also herd but less intensively, since the overall administrators are not so narrowly compared with each other by either markets or regulators. The least intense herding occurs among funds within PFAs, where competition is little as the incentives for PFAs is to keep pensioners within the PFA, in any fund. Fourth, we do not find evidence that momentum trading is the main cause of the herding observed in domestic assets. Fifth, although the patterns found in this paper might be influenced by certain aspects of the regulation that make funds across PFAs compare with each other, the investment decisions of fund managers cannot be neglected since, among other things, there is no specific mandate for pension funds to trade in specific securities and herding does not decrease when regulations are relaxed. Moreover, the behavior does not seem to be explained by the lack of investable instruments because pension funds do not even invest in all of the available and pre-approved assets.

The findings on herding have implications for the general debate on capital market development. One key motivation for countries to promote institutional investors in general, and pension funds in particular, has been the expectation that they would play a dynamic role in the development of capital markets. This motivation has been particularly important in developing countries.[5] In many respects, pension funds might be better equipped than other institutional investors to have a positive impact on capital markets. Since pensioners save for the long run and provide a steady flow of funds, pension funds (unlike other institutional or retail investors) are expected to be able to provide stable long-term financing to domestic corporations as well as governments. Moreover, considering 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 that pervade financial markets. Also, given that pension funds usually face regulatory requirements to allocate a large fraction of the assets under management domestically and given that they tend to accumulate large capital, they could invest in a relatively broad range of (pre-approved) 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 that contribute the most to the development of domestic capital markets by, among other things, investing in different types of securities, providing liquidity, knowing the markets, and pursuing investment strategies with long-term goals.

Despite the initial expectations, the actual impact that the increasing prominence of pension funds has had on the development of local capital markets in developing countries is still subject to 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 add to the liquidity of these markets through their trading activity.[6] Others

---

[5] Davis (1995) argues that pension funds 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 capital market innovation, competition, and efficiency. Impavido et al. (2003) find that the institutionalization of savings increases market depth and in some cases improves stock market liquidity. Also see Piñera (1991), Vittas (1995 and 1999), Reisen (2000), Blommestein (2001), Davis and Steil (2001), and de la Torre and Schmukler (2006), among others.

[6] See Davis (1995), Vittas (1995 and 1999), Catalán et al. (2000), Lefort and Walker (2000, 2002a, and 2002b), Corbo and Schmidt-Hebbel (2003), Catalán (2004), and Andrade et al. (2007).

maintain that pension funds do not contribute as expected to the development of capital markets, and are not investing pensioners' savings optimally.[7] The types of patterns documented in this paper contribute to this debate. They do not seem fully consistent with the initial expectations that pension funds would be a dynamic force stimulating the overall development of secondary capital markets. Pension funds may ease the access of some firms to funds through equity or bond primary issuances and thus have a positive effect on the development of primary capital markets. But their degree of herding, both in the buying and selling side, suggest that pension funds might contribute less than expected to the liquidity of different markets, price formation, or the provision of distinct alternative investment vehicles for pensioners.[8]

The rest of the paper is structured as follows. Section 2 very briefly summarizes the main features of the case of Chile and its pension fund system. Section 3 describes the data and some basic turnover statistics. Section 4 studies different turnover measures. Section 5 explores what other factors might be related to herding behavior. Section 6 concludes.

2. Chile's Pension Fund System

Chile is a good natural case study to analyze in depth the behavior of pension funds and, more broadly, institutional investors. Chile not only introduced the new pension fund system, but also continuously improved the regulatory environment such that pension funds become better investment vehicles for pensioners. At the same time, it also fostered the development of mutual funds and insurance companies as alternative and complementary investment vehicles. Aside from reforming the institutional investor base, Chile has more broadly implemented and

[7] See Arrau and Chumacero (1998), Zurita (1999), IMF and World Bank (2004), Olivares (2005), Yermo (2005), Berstein and Chumacero (2006), and The Economist (2008).

[8] Moreover, pension funds invest heavily short term. Opazo et al. (2009) show that Chilean pension fund portfolios are short term relative to those of insurance companies and US mutual funds.

succeeded in a series of macroeconomic and institutional policies to achieve a stable market-friendly economy, where capital markets play an important role and investors have incentives to participate. Furthermore, as mentioned in the Introduction, among many countries, Chile has been regarded as the example to follow in terms of pension fund and capital market reforms.

In 1980, Chile decided to reform its pension fund system and replaced over time 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). 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. 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.

Over time, the system became more flexible as investment regulations were relaxed and choices increased. During the first ten years of the system, each PFA managed a unique fund offering no choice to 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). Each fund type is subject to different restrictions on its asset allocation. Therefore, the entire set of funds offers more flexibility through different risk-return combinations, 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.

The mandate of each pension fund is to provide the highest possible returns to pensioners given the set of risk parameters and investment regulations. There are no restrictions on the amount and type of trading activity and they do not operate like individual life-cycle funds. Their mandate differs from that of life insurance companies that need to meet the (typically long-term) obligations stipulated in the insurance contracts. Pension fund managers, on the other hand, do not have liabilities with the pensioners; they simply manage their assets.

Chilean pension fund administrators invest in different assets subject to a set of quantitative restrictions that are defined by law and that specify how much pension fund administrators are allowed to invest in specific instruments. Pension funds can only invest in assets listed in the pension law and traded in public offerings. These investment limits have been relaxed over time, incorporating quantitative and conceptual changes. However, these limits do not seem to have been binding (except for the case of foreign investments which reached the limit over time). During the period 2002-2005, PFAs invested in only a subset of the assets approved for investment by the Risk-Rating Commission (*Comisión Clasificadora de Riesgo*, CCR). For example, during this period they invested in 65-72 percent of all the approved equity and in 15-18 percent of all the approved foreign mutual funds. Within a PFA, pension fund portfolios are managed separately, but the PFA provides market analysis and asset recommendations to all its funds, resulting in some correlation on portfolio compositions.[9]

Aside from the investment restrictions, 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 of the same type (i.e., Funds C are benchmarked with other Funds C) minus two percentage points for

[9] Most PFAs have managers that specialize in broad asset classes (fixed income and variable income) and participate in the construction of the portfolios of each of the funds.

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 of the same type, whichever is lower. The average real rate of return to calculate the minimum return changed from 12 months to 36 months in October 1999, giving PFAs more flexibility to deviate in the short term from the industry comparators.[10] This type of regulation can be found in other countries and, as shown below, it cannot be the only factor determining the behavior of pension funds since there is not a clear change in behavior after the regulation is relaxed.[11]

After the introduction of the multi-fund scheme in August 2002, investment limits per instrument set by the central bank did not change for domestic instruments in the 2002-2005 period, but were relaxed twice for foreign investments (an additional relaxation took place in August 2002). Limits on domestic fixed-income (variable-income) instruments gradually increase (decrease) as funds become less risky (i.e., when one moves from Fund A toward Fund E).[12]

Over time, pension fund administrators have grown substantially and have become the largest institutional investors in Chile. Assets under pension fund management increased substantially both in absolute and relative terms. In 2005, pension funds managed around 75 billion dollars, an amount that was almost 2.5 times the 1996 value in real terms. As a share of

[10] 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.

[11] The use of a minimum return band is not specific to Chile; most Latin American countries with a defined-contribution pension fund system offer guaranteed minimum returns, either relative or absolute. For instance, Colombia, Dominican Republic, El Salvador, Peru, and Uruguay guarantee these minimum returns, and funds are required to maintain reserves to meet these guarantees in case of underperformance. Among major reformers, only Mexico does not guarantee a minimum return.

[12] 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. For foreign investments, the limit is set at the PFA level and was relaxed twice during 2003. The maximum allowed by law is 30 percent of the value of all funds managed by a single PFA.

GDP, assets managed by pension funds increased by 1.85 times, from 38 percent in 1996 to 71 percent in 2005. Since their inception in 1981 and 2005, pension funds grew at an average annual rate of 28 percent in GDP terms. Furthermore, pension funds held around ten percent of equity market capitalization (which 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. Figure 1 shows the evolution of pension system holdings as a share of GDP.

As assets under management expanded, the industry consolidated. 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 that took place mostly in the late 1990s. Since the number of pension funds in the market has been proportional to the number of PFAs, the number of pension funds increased from 15 (one per PFA) to 30 (five per PFA) from July 1996 to December 2005.

3. Data and Turnover Statistics

The data used in this paper come from Chile's Superintendency of Pensions (*Superintendencia de Pensiones, SP*) and consist of a panel of all the portfolio investments of PFAs in operation, for each of their funds, during the period July 1996 to December 2005 at a monthly frequency, including information on returns. In other words, the dataset has information 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 the dataset, we use 3,869,290 observations, representing all domestic fixed income securities and domestic equity held during each month by at least one fund.

The dataset contains information on the holdings of 24,322 different securities, for up to 57 funds, at a monthly frequency. These securities are divided into 20 different instrument types. We group all the instrument types into five general asset classes: corporate bonds, financial institutions bonds, government bonds, mortgage bonds, and equity.[13,14] The average portfolio holding in each class by type of fund is displayed in Table 1.

The securities analyzed in this paper vary across different dimensions associated with the availability of market information on issuing companies and the availability of quoted and realized market prices for institutional investors. Table 2 shows some characteristics of issuances, trading activity, and size of issuers for the key assets classes analyzed in this paper: corporate bonds (including those issued by financial companies, which tend to be similar to corporate bonds), government bonds, and equity.[15] During the sample period, issuance per year is highest for corporate bonds, then government bonds, and lastly equity (Panel A). This is expected since many companies issue bonds, and they have to continue issuing them over time as bonds mature and firms seek refinancing. But the amount issued in corporate bonds per company is much smaller than the total amount issued by the government, and similar to the equity issued per company.[16] Panel B shows data on turnover ratios (annual value traded divided by end-of-

[13] The original data also contain information on the holdings of derivatives, investment and mutual fund quotas, former pension system bonds, deposits, and foreign assets, but we exclude them from the analysis for various reasons. For instance, former pension system bonds are securities that were issued to the workers that moved from the old pay-as-you-go system to the new pension system when the reform was implemented in 1981. Thus, they are highly idiosyncratic and are increasingly disappearing as the system matures. Also, while quotas of investment and mutual funds are variable income instruments, the underlying assets are in many cases fixed-income (bond funds) or a combination of bonds and equity, so they cannot be easily mapped into the standard categories. Foreign assets are excluded because, for regulatory reasons, most foreign investment carried out by Chilean pension funds occurs through the purchase of quotas of foreign investment funds.

[14] While mortgage bonds (*letras hipotecarias*) represent 73.3 percent of the observations, they only stand for 19.6 percent of the investment when considering the entire period 1996-2005.

[15] In this table, corporate bonds and financial institutions bonds are grouped together for data availability reasons.

[16] The median amounts per issue are smaller for corporate bonds than for equity, since companies typically issue several series of a corporate bond. Median amounts per issue for government bonds are small because the government tries to issue regularly to provide liquidity to the market and establish the benchmark yield curve.

the-year market capitalization) across these three asset classes. Clearly, government bonds are the asset class with the highest turnover, followed by equity, and corporate bonds. Government bonds and equities not only have higher turnover than corporate bonds, but also are more frequently traded in open exchanges (Panel C). For instance, equities from the 40 listed companies that compose the main Chilean stock market index (IPSA) (where pension funds invest most of their equity portfolio) traded on average 92 percent of the trading days in 2004. Government bonds of maturities between 8 to 10 years also traded almost every day. In contrast, corporate bonds of intermediate maturities (8-10 years) traded 46 percent of the time during that year.[17] Finally, companies listed in the stock exchange are typically larger than those that issue corporate bonds. Panel D compares the median size of the main listed companies and of those companies that have issued corporate bonds. It shows that, despite corporate bond issuers being relatively large in Chile, they are typically smaller than the main companies listed in the stock exchange (median assets of US$ 750 million versus US$ 1,900 million for listed firms in 2005). Even the 40 largest companies with corporate bonds outstanding during 2002-2005 are smaller than the 40 main listed companies included in the IPSA (median assets US$ 1,700 versus US$ 1,900 million in 2005).

In summary, the data show that government bonds are widely available, frequently traded, and have easily available price information. Equity markets are dominated by large corporations, whose stocks trade frequently in open exchanges. Corporations issuing corporate bonds are smaller than those issuing equity, issuances are large, but they are infrequently traded and a non-trivial part of this activity occurs over the counter. These differences suggest that

However, this should not make each issuance less transparent since the underlying debtor is the same. Summary statistics on amounts per issue are not reported, but are available upon request.

[17] Data on the trading frequency of corporate and government bonds come from Lazen (2005). Trading frequency for equities come from the Santiago Stock Exchange.

corporate bonds are probably the most opaque of the Chilean asset classes, followed by equity and finally government bonds.

To complement the analysis, we display here some basic measures of turnover or trading activity by pension funds of different types of securities. Turnover is generally related to market liquidity, which is vital for the emergence of new instruments, capital raising activity, and the functioning of secondary markets. More trading reduces the cost of immediate execution, lowering bid-ask spreads and reducing firm's opportunity cost of capital.[18]

Table 3 Panel A shows that pension funds tend to trade infrequently. In particular, Panel A shows what fraction of its assets a given PFA trades at any moment in time. The table presents two simple statistics: the number of total assets traded by a PFA in a given period relative to the total number of holdings in the PFA's overall portfolio (column 1) and the value of the aggregate portfolio that experiences some activity in a given month (column 2), both averaged over time.[19] On average, a PFA trades only 13 percent of its assets and the monthly changes in positions in those assets correspond to just four percent of the initial total value of the PFA's assets. This low number contrasts with the 88 percent of the mean turnover ratio found in Kacperczyk et al. (2008) for a sample of 2,543 actively managed US equity mutual funds between 1984 and 2003, suggesting that Chilean PFAs are rather passive in their trading behavior. There is important variation across asset classes in the degree of PFA trading activity. The most traded assets are equities and mortgage bonds. On the other hand, there is a low degree of trading in corporate and financial institution bonds.[20]

[18] See, for example, Amihud and Mendelson (1986), Chordia et al. (2001), and Bekaert et al. (2007).

[19] 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.

[20] 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

An alternative 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 and collect coupons in the meantime. Table 3 Panel B 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. They show that, on average, PFAs purchase most of their fixed-income assets at once and liquidate most of them upon maturity, not before. That is, although pension funds might hold a large fraction of the outstanding securities, they trade a small fraction of them in secondary markets. This buy-and-hold behavior is common in this type of institutional investors, although it runs contrary to the idea that pension funds would provide liquidity to secondary markets. Nonetheless, even in fixed-income assets, pension funds still trade between 5 to 10 percent of their holdings over the lifetime of the asset.

4. Do Pension Funds Herd?

To formally test for the presence of herding we compute different estimates of herding. These measures focus on whether funds simultaneously buy or sell the same assets in a given moment. We measure the degree of 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

---

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, in order to reinvest them, PFAs need 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.

among assets being traded. 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:

$$H(i,t) = \left|\frac{B(i,t)}{N(i,t)} - p(t)\right| - AF(i,t), \qquad (3)$$

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. 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.

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 on the right-hand side of equation (3) 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 zero mean.[21]

The adjustment factor $AF(i,t)$ is $AF(i,t) = E(|p(i,t) - E[p(i,t)]|)$, 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.

[21] We compute tests for the average $H(i,t)$. When divided by its standard deviation, this random variable follows a t distribution under the law of large numbers.

In what follows, we focus on measures per asset class, where we compute different probabilities of buying an asset ($p(t)$) for each asset class because of the large differences in trading activity across asset classes reported in Tables 2 and 3.

As explained above, our data have information on the detailed portfolios of all pension funds managed by the universe of pension fund administrators (PFAs). Furthermore, we know which PFA manages each of the funds. We use this information to test for the presence of herding at four levels of aggregation. First, we test for herding at the PFA level (aggregating all funds managed by a PFA in a single portfolio). This neglects within-PFA herding and only considers herding among administrators. Second, we also test for herding at the PFA-fund level, which considers both herding within and across administrators. Two or more funds within a PFA or across PFAs buying the same asset would equally contribute to this herding statistic. Third, we consider herding at the within-PFA level, which only looks at whether funds managed by the same PFA tend to buy/sell the same assets. Finally, we test for the presence of herding across PFAs, but within a given fund type. Only funds of the same type (from A to E) trading the same assets count for the computation of the statistic. Testing for herding at these different levels of aggregation provides valuable information on the determinants of herding and the incentives that managers have to engage in this behavior. The results of these exercises follow.

Table 4 reports herding results at the PFA level, with each entry displaying the mean of the herding statistic for each asset class and its corresponding standard error, using an asset-class-specific probability of buying an asset. Column (1) presents the results obtained computing the statistic across all assets traded by more than one PFA. To show the robustness of the results to different estimates of herding, columns (2) and (3) report the herding statistics computed over those assets traded by more than two and three PFAs. 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, conditional on trading them, is 51 percent and the average probability of buying mortgage bonds is 13 percent.

The results in Table 4 show that there is robust evidence of herding, both overall and across asset classes. Except for government bonds traded by more than one PFA, one observes positive and statistically significant coefficients regardless of the number of PFAs trading a given asset. The results also show significant differences in the coefficients of herding across asset classes within each column. Herding seems to be stronger for corporate bonds and financial institutions bonds. This ranking of herding across asset classes closely resembles the differences in market transparency of different asset classes documented in Section 3. As shown in Table 2, while Chilean corporate bonds are typically issued by relatively large companies, they are much less frequently traded than equities and government bonds, and part of these trades occur in more opaque over-the-counter markets rather than in open exchanges.[22]

Except in the case of mortgage bonds, the different columns show that the prevalence of herding increases 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 corporate bonds is 14 percent when considering assets traded by more than three PFAs, up from ten percent when considering assets traded by

[22] Some existing papers propose that financial institutions bonds are more opaque than standard corporate bonds (Morgan, 2002). However, more recent papers have shown that large banks are not more opaque than comparable corporations (Flannery et al., 2004). In Chile, only large banks issue corporate bonds, so one should not expect a large difference in opacity between these two asset classes.

more than two PFAs, and up from three percent when considering assets traded by more than one PFA. In the case of mortgage bonds, we find less herding for the measures that consider bonds traded by more PFAs. This result is expected since the number of specific mortgage bonds in the markets is very large, with each bond being small. Therefore, the probability of a mortgage bond being traded by more than two PFAs is small.

Overall, the results indicate that the presence of herding among Chilean PFAs in many asset classes increases as an asset is being traded by more PFAs. In other words, although PFAs trade in few assets, when various PFAs are active they tend to be on the same side of the trade.

Table 5 reports similar herding estimates than Table 4 (i.e., at the PFA level) but constraining the sample to the multi-fund period, 2002-2005, when more funds become available. The results show that herding is still prevalent among corporate bonds and financial institutions bonds but significantly less so in other asset classes, except for a couple of instances for mortgage bonds and government bonds. Again, as assets are traded by more PFAs the herding statistics increase. The differences in results between Table 4 and Table 5 suggest that part of the herding might be driven by competition between pension funds, not PFAs, since herding is stronger when including the period for which only one/two funds per PFA are available (Table 4).[23] As the number of funds within PFAs increases, the degree of herding across asset classes diminishes.

Given that part of the herding seems to be explained by trading at the fund level, Table 6 shows herding statistics using all funds across PFAs, without distinguishing the PFA or type to which each fund belongs. That is, this herding measure is computed at the most disaggregate level, taking into account the within PFA and across PFA variation, across any type of fund. The

[23] During 1996-1999, pension funds administrators offered a single fund (corresponding to Fund C in the current classification), and during 2000-2002 they offered two funds (corresponding to Funds C and D in the current classification).

results in Table 6 show again that herding is more prevalent in corporate bonds and financial institutions bonds. However, the point estimates are noticeably smaller than in Table 5. For example, in the case of corporate bonds traded by more than three PFAs, the herding statistic in Table 6 is 4.58 while that in Table 5 is 20.55. The only result that does not follow this pattern is the degree of herding in equities, for which coefficients become statistically significant in Table 6. In other words, part of the herding in equities is explained by the fund-level behavior. Since different fund types face different regulatory limits on their portfolio allocations, it is not surprising that the herding statistic is lower when considering the trades conducted by different fund types (since they would be investing in different asset classes). However, these differences in regulatory constraints cannot fully account for the observed decline in herding because they only restrict the composition of a fund's portfolio across asset classes. Whereas these constraints could reduce the degree of overall herding computed by pooling all asset classes, as Table 6 shows, the decline in herding occurs within each asset class. Overall, while the results in Table 6 suggest that fund-level herding is important, they leave unanswered the question of how funds specifically interact with each other in their trading and herding activity. We explore this issue in the next set of tables.

Table 7 reports results of herding among funds within PFAs. As above, the comparison within asset classes eases concerns about the different compositions of the portfolios of different types of funds. While one still observes significantly more herding for corporate bonds and financial institutions bonds, the herding statistics are also significant for government bonds and, in one instance, for mortgage bonds. These results hold when assets are traded by more than two and more than three funds. The results suggest then that part of the herding in government bonds is driven by PFAs purchasing those securities for several of their funds. In fact, PFAs participate actively in government bond auctions, demanding a significant proportion of the securities that come to markets (Opazo et al., 2009).

Table 8 shows results by comparing funds within fund types across PFAs. Interestingly, the herding statistics increase noticeably across the board in this case, both in terms of the point estimates and the statistical significance of the coefficients. For example, relative to the estimates at the PFA level, the average herding across asset classes in Table 8 is 5.80 for assets traded by more than two funds, vis-à-vis 4.02 in Table 5, and 5.22 for assets traded by more than one fund, vis-à-vis 2.00 in Table 5. The asset classes that experience more herding are corporate bonds and financial institutions bonds. The ones that experience less herding are government bonds and mortgage bonds. Equity is in the middle. What is also clear from this table is that the herding in equity is driven almost exclusively by herding within fund types across PFAs. Table 9 decomposes herding by type of fund and shows that the within fund type herding is not due to herding in only one fund type. Instead, herding within fund types across PFAs occurs across all types of funds.

As mentioned in Section 3, pension funds tend to purchase fixed income securities at issuance and hold them until maturity. The herding statistics reported above do not include the dates when instruments are removed from the markets. So they are not affected by the maturing fixed income instruments. However, they do include initial purchases at issuance. While this does not pose a bias to the estimates, it raises the question of whether herding is driven mainly by these initial acquisitions. To answer this question, we re-compute the herding statistics excluding purchases at issuance for fixed income assets. We do so for the estimates at the PFA level and within fund types across PFAs, reported in Tables 10 and 11, respectively. Relative to Table 4, the estimates in Table 10 show that herding is prevalent even after the purchases at issuance, when securities are bought in secondary markets.[24] However, as expected, the herding estimates for fixed income securities are lower when initial acquisitions are removed from the sample. Relative to the previous tables, the ranking of herding across asset classes holds. The comparison between Tables 8 and 11 yield similar conclusions.

To further understand where the trading behavior is coming from, we decompose herding into herding in buying and herding in selling following Grinblatt et al. (1995). Again, we do so for estimates at the levels of the PFAs and within funds across PFAs, reported in Tables 12 and 13, respectively. In general, the results suggest that herding occurs at both sides of the transactions. That is, pension funds herd both when they purchase securities and when they sell them in secondary markets. The only exception is the case of mortgage bonds that show herding only on the buy side. This might be due to pre-payment and restructuring of those bonds, which might lead pension funds to remove them from their portfolios at different points in time.

5. What Other Factors Might Be Related to Herding?

In this section, we explore what other factors might be associated with the herding behavior documented above. In particular, we explore first whether pension funds herd only when they contemporaneously trade securities. Then we discuss whether herding is explained by momentum trading, regulation, or the availability of assets.

Aside from the herding studied above, which refers to *contemporaneous herding*, there can also be *dynamic herding*, which is related to whether funds follow the herd with a lag. Therefore, assets that are more heavily traded in a given period are also more likely to be traded

[24] These results may slightly overestimate the role of purchases at issuance. The reason is that we do not have the issuance date for the fixed income assets, so we assume that it corresponds to the date when the assets first appear in our dataset. This is a good approximation because PFAs tend to quickly absorb fixed income assets in their portfolio. According to market participants, PFAs actively demand assets during the underwriting process. However, it is possible than in a few cases we may exclude the first purchase of an asset in secondary markets.

in subsequent moments. This dimension of herding is studied by Sias (2004), who tests the hypothesis that assets that are traded in a given period are more likely to be traded in subsequent moments or that the intensity of trading is serially correlated. We do so by estimating the parameters β_t in the following equation for each month t:

$$\Delta_{i,t} = \beta_t \Delta_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

where $\Delta_{i,t} = \frac{Raw_{i,t} - \overline{Raw}_t}{\sigma(Raw)_t}$, $Raw_{i,t}$ 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.[25]

Table 14 reports the results on dynamic herding. Each entry in the table reports the average β_t across months for various asset classes, its standard error, and the fraction of periods in which the coefficient is significantly different from zero at a 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

[25] The reason Sias (2004) standardizes the statistics is that it conducts inference on β_t based on the time-variation of the parameters only (à 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.

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.

As mentioned in the Introduction, aside from herding, there can also be momentum trading. In fact, in Raddatz and Schmukler (2008), we show evidence of momentum. 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. 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*.

The previous results on herding might be explained by momentum trading. If funds chase returns, they would tend to buy assets when their returns are positive and look like they are following each other, when instead they are following returns. However, the results from Table 15, which regresses herding on lagged returns, suggest that momentum trading does not explain herding. In particular, the herding statistics are unrelated to the lagged returns of the assets included in each class. In unreported results, the same conclusions are reached if one analyzes dynamic herding instead. This suggests that herding behavior does not seem to be driven by managers' common preferences over asset characteristics, such as stocks with high past returns.

Regulation might also play a role in the findings on herding. Chilean PFAs are subject to a minimum return requirement relative to the average return that may induce fund managers to mechanically herd around the average portfolio to avoid penalties. The time variation of the herding measures can be used to determine the impact of changes in regulation. In October 1999, the average real rate of return to calculate the minimum return changed from 12 months to 36 months. This greater flexibility was expected to reduce the degree of herding, because the reform has given managers more time to converge to the average return. Nevertheless, the data show no evidence of a decline in herding around the date of the reform. Table 16 compares the herding statistics computed in a window of 18 months before and after October 1999 for each asset class. For most asset classes, instead of a decline, we observe an increase in the herding statistic after the reform. Only among mortgage bonds, there is evidence of a small decline in herding. Thus, these findings do not support the claim that herding was mainly due to the tightness of the regulatory band. Note, however, that this is very indirect test of herding and that other factors might have influenced the degree of herding at that time. Furthermore, it is possible that the band affected the degree of herding initially and that once pension funds engage in this type of behavior, to be close to their peers, it might be difficult to deviate.

In addition, we analyze the possibility that herding behavior may be driven by the regulatory minimum return band by comparing the degree of herding observed across funds that face different regulatory bands according to their risk profiles. Although the band is typically larger for riskier funds, groups of funds with different risk profiles (i.e., funds investing different shares of their portfolios in riskier assets) 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; for funds A and B the band is of four percentage points. Intuitively, a given size of regulatory band should be more binding for riskier funds because of their higher absolute return volatility. Thus, we would expect to observe more herding in fund C than in D and E, and in A relative to B.[26] The results shown in Table 9 above tend to support this prediction. When

[26] The idea is simply that funds investing in riskier assets will have a higher degree of idiosyncratic volatility if they do not follow the herd, making them more likely to hit the regulatory band. On the other hand, if they always follow the crowd, all risk in their portfolios would be aggregate risk. So, even if their absolute returns are volatile, their relative returns would not.

considering herding over all asset classes the table shows that herding in Fund A is larger than that in Fund B. Moreover, herding in Fund C is higher than that in Fund D, which in turn is higher than that in Fund E. Note that the pattern in Table 9 cannot simply result from a relation between the riskiness of assets and herding. If that were the case, there should be a decreasing degree of herding as the riskiness of the portfolio declines from fund type A to fund type E. Instead, the decreasing relation occurs only across funds that face similar regulatory bands. This suggests that regulations that lead funds to follow industry benchmarks, such as a minimum return band, might impact the way that funds behave and induce herding. In sum, the evidence provides only mixed support to the idea that aspects of the regulation may contribute to herding among pension funds.

Finally, the herding results are also not driven by the lack of available instruments. This conclusion can be reached by comparing 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 invest. On average, PFAs invest only in a subset of the available assets, 47 percent for the case of corporate bonds. This suggests that herding is not driven by the fact that all PFAs purchase the same assets when they become available because they have already exhausted the supply of investable assets. On the contrary, they select the same assets at the same time from a wide range of alternatives. Similar conclusions can be reached if one looks at the auctions of government paper and the biddings by PFAs in those public offerings (Opazo et al., 2009).

6. Conclusions

Using unique pension fund data from Chile, this paper advances our understanding of herding behavior and, more generally, the investment practices of institutional investors. In particular, the paper exploits the richness of the data to test for and characterize herding behavior among pension funds across different asset classes and levels of the industry. In doing so, it sheds important light on the underpinnings of herding, and on the consequences that the emergence of institutional investors might have for capital market development.

The paper shows that pension funds herd significantly in their investment decisions. In particular, herding is more pronounced on instruments that are more opaque, suggesting that pension funds copy each other in their investment decision as a way to overcome informational problems. Thus, herding is more prevalent in corporate and financial institutions bonds, followed by equity and government bonds. This ranking of herding across asset classes is robust across the different levels of disaggregation we analyze (PFA level, PFA-fund level, and so forth). These findings are consistent with the view that asset characteristics matter for herding, and highlight an important shortcoming of the existing literature on herding in that it typically focuses on a particular asset class. The large prevalence of bonds in the portfolios of many institutional investors and the differences we document on the presence of herding in corporate bonds relative to equity suggest that existing evidence solely based on equity may lead to incorrect conclusions about the magnitude and potential consequences of herding. For example, the recent US experience with correlated exposure of institutional investors on mortgage-backed securities indicates that the potential destabilizing consequences of herding may be large.

Our results also shed some light on the relation between competition and herding. We find that herding is more intense when comparing similar types of funds across PFAs than when comparing aggregate PFA portfolios. Narrowly defined fund types are easily compared by the public, the regulator, the overall managers of PFA, and peers, and thus compete directly with each other across PFAs (each PFA can only have one fund of each type). PFAs also compete among them, but since the relative size of each fund type may vary across funds it is more difficult to compare them. Furthermore, we also find less evidence of herding when considering all PFA-funds together and when comparing various fund types within the same PFA. These results are consistent with herding being driven by incentives faced by managers to be with the pack of their direct competitors and not deviate from industry standards. Thus, contrary to expectations, under certain conditions (such as the existence of relative industry-benchmarks), competition, understood as having a clear set of peers fighting for a certain market, may increase the incentives to herd rather than yield more healthy, dispersed behavior.

Overall, the data indicate that the incentives of institutional investors to herd and not deviate from the pack seem to come from the complex interaction between the opaqueness and risk of the assets in which they invest, the endogenous and regulatory driven use of industry benchmarks (not exclusive to the Chilean case), and the existence of a clearly defined group of competitors. Pension funds are usually regulated and monitored to protect pensioners' assets. To avoid misbehavior, managers are continually evaluated by investors, regulators, and their own managers against deviations from a benchmark, which might induce them to herd and stay close to their peers regardless of absolute returns. Furthermore, while regulations might promote herding by establishing bands within which returns across funds have to lie, the evidence presented here shows that herding does not decrease when regulations are loosened. More generally, investors and regulators face a trade-off between the need for monitoring asset managers on a regular basis and giving them incentives and space to engage in long-term arbitrage and asset discovery. These incentives on asset allocation by pension funds and other institutional investors might be important and have been typically overlooked by the literature.

In addition to the lessons offered by our results on the determinants of herding, the patterns described in the paper seem to run contrary to the initial expectations in emerging markets about the role of pension funds as drivers of secondary 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 bonds and effectively contributing to the development of that market. However, the characterization 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. Consider that these are likely to be the most sophisticated investors in the market, especially in developing countries, with plenty of resources to gather private information and manage the portfolios professionally. Instead, the high degree of herding behavior is consistent with funds following each other in their investment strategies. Moreover, herding behavior does not seem to be explained by the lack of investable instruments because pension funds invest only in a fraction of the existing and pre-approved assets. In addition, pension funds tend to display relatively little turnover, which does not seem to square well with the idea that they contribute to the liquidity of secondary markets. Overall, the evidence suggests 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.

References

Andrade, L., D. Farrell, and S. Lund, 2007. Fulfilling the Potential of Latin America's Financial Systems, *McKinsey Quarterly*.

Amihud, Y. and H. Mendelson, 1986. Asset Pricing and the Bid-Ask Spread, *Journal of Financial Economics* 17(2), 223-249.

Arrau, P. and R. Chumacero, 1998. Tamaño de los Fondos de Pensiones en Chile y su Desempeño Financiero, *Cuadernos de Economía* 35(105), 205-235.

Badrinath, S.G. and S. Wahal, 2002. Momentum Trading by Institutions, *Journal of Finance* 57(6), 2449–2478.

Banerjee, A.V., 1992. A Simple Model of Herd Behavior, *Quarterly Journal of Economics* 107(3), 797-817.

Bekaert, G., C.R. Harvey, and C. Lundblad, 2007. Liquidity and Expected Returns: Lessons from Emerging Markets, *Review of Financial Studies* 20(6), 1783-1831.

Berstein, S.M. and R.A. Chumacero, 2006. Quantifying the Costs of Investment Limits for Chilean Pension Funds, *Fiscal Studies* 27(1), 99-123.

Bessembinder, H. and W. Maxwell, 2008. Transparency and the Corporate Bonds Market, *Journal of Economic Perspectives* 22(2), 217-234.

Bikhchandani, S., D. Hirshleifer, and I. Welch, 1992. A Theory of Fads, Fashion, Custom, and Cultural Change in Informational Cascades, *Journal of Political Economy* 100(5), 992-1026.

Blake, D., B. Lehmann, and A. Timmermann, 2002. Performance Clustering and Incentives in the UK Pension Fund Industry, *Journal of Asset Management* 3(2), 173-194.

Blommestein, H., 2001. Ageing, Pension Reform, and Financial Market Implications in the OECD Area, CeRP Working paper 9/01.

Bolton, P., J. Scheinkman, and W. Xiong, 2006. Executive Compensation and Short-Termist Behavior in Speculative Markets, *Review of Economic Studies* 73(3), 577-610.

Catalán, M., 2004. Pension Funds and Corporate Governance in Developing Countries: What Do We Know and What Do We Need To Know? *Journal of Pension Economics and Finance* 3(2), 197-232.

Catalán, M., G. Impavido, and A.R. Musalem, 2000. Contractual Savings or Stock Market Development: Which Leads? *Journal of Applied Social Science Studies* 120(3), 445-487.

Chevalier, J. and G. Ellison, 1999. Career Concerns of Mutual Fund Managers, *Quarterly Journal of Economics* 114(2), 389-432.

Choi, N. and R.W. Sias, 2009. Institutional Industry Herding, *Journal of Financial Economics* 94(3), 469–491.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001. Market Liquidity and Trading Activity, *Journal of Finance* 56(2), 501-530.

Corbo, V. and K. Schmidt-Hebbel, 2003. Macroeconomic Effects of the Pension Reform in Chile, in Pension Reforms: Results and Challenges, ed. International Federation of Pension Fund Administrators, 241–329, Santiago, Chile.

Dahlquist, M., L. Pinkowitz, R. Stulz, and R. Williamson, 2003. Corporate Governance and the Home Bias, *Journal of Financial and Quantitative Analysis* 38(1), 87-110.

Davis, E.P., 1995. Pension Funds: Retirement Income Security and Capital Markets-An International Perspective, Oxford University Press, Oxford.

Davis, E.P. and B. Steil, 2001. Institutional Investors, MIT Press, Cambridge, MA.

de la Torre, A. and S. Schmukler, 2006. Emerging Capital Markets and Globalization: The Latin American Experience, Stanford University Press and World Bank.
Eterovic, D., A. Silva, and C. Oyarzun, 2011. El Mercado de Renta Fija en Chile. Departamento de Estudios Larrain Vial, Santiago, Chile.
Fama, E.F. and J.D. MacBeth, 1973. Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81(3), 607-636.
Ferson, W. and K. Khang, 2002. Conditional Performance Measurement Using Portfolio Weights: Evidence for Pension Funds, *Journal of Financial Economics* 65(2), 249-282.
Flannery, M.J., S.H. Kwan, and M. Nimalendran, 2004. Market Evidence on the Opaqueness of Banking Firms' Assets, *Journal of Financial Economics* 71(3), 419-460.
Froot, K.A., D.S. Scharfstein, and J.C. Stein, 1992. Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation, *Journal of Finance* 47(4), 1461-1484.
Gompers, P.A. and A. Metrick, 2001. Institutional Investors and Equity Prices, *Quarterly Journal of Economics* 116(1), 229-259.
Graham, J.R., 1999. Herding Among Investment Newsletters: Theory and Evidence, *Journal of Finance* 54(1), 237-268.
Greenwood, R. and S. Nagel, 2009. Inexperienced Investors and Bubbles, *Journal of Financial Economics* 93(2), 239–258.
Grinblatt, M. and M. Keloharju, 2000. The Investment Behavior and Performance of Various Investor Types: a Study of Finland's Unique Data Set, *Journal of Financial Economics* 55(1), 43-67.
Grinblatt, M., S. Titman, and R. Wermers, 1995. Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior, *American Economic Review* 85(5), 1088-1105.
IMF and World Bank, 2004. Financial Sector Assessment Program. Chile: The Pension Fund Sector, IMF Country Report 04/269.
Impavido, G. and A.R. Musalem, 2000. Contractual Savings, Stock, and Asset Markets, World Bank Policy Research Paper 2490.
Impavido, G., A.R. Musalem, and T. Tressel, 2003. The Impact of Contractual Savings Institutions on Securities Markets, World Bank Policy Research Paper 2948.
Kacperczyk, M., C. Sialm, and L. Zheng, 2005. On the Industry Concentration of Actively Managed Equity Mutual Funds, *Journal of Finance* 60(4), 2379-2416.
Kacperczyk, M., C. Sialm, and L. Zheng, 2008. Unobserved Actions of Mutual Funds, *Review of Financial Studies* 21(6), 2379-2416.
Kaminsky, G., R. Lyons, and S. Schmukler, 2004. Managers, Investors, and Crises: Mutual Fund Strategies in Emerging Markets, *Journal of International Economics* 64(1), 113-134.
Kapur, S. and A. Timmermann, 2005. Relative Performance Evaluation Contracts and Asset Market Equilibrium, *Economic Journal* 115(506), 1,077-1,102.
Lakonishok, J., A. Shleifer, and R.W. Vishny, 1992. The Impact of Institutional Trading on Stock Prices, *Journal of Financial Economics* 32(1), 23-43.
Lazen, V., 2005. El Mercado Secundario de Deuda en Chile. Documento de Trabajo N°5, Superintendencia de Valores y Seguros, Santiago, Chile.
Lefort, F. and E. Walker, 2000. The Effects of Economic and Political Shocks on Corporate Governance Systems in Chile, *Revista ABANTE* 2(2), 183-206.

Lefort, F. and E. Walker, 2002a. Premios por Plazo, Tasas Reales y Catástrofes: Evidencia de Chile, *El Trimestre Económico* 69(2), 191-225.
Lefort, F. and E. Walker, 2002b. Pension Reform and Capital Markets: Are There Any (Hard) Links? World Bank Social Protection Discussion Paper 0201.
Livingston, M., A. Naranjo, and L. Zhou, 2007. Asset Opaqueness and Split Bond Ratings, *Financial Management* 36(3), 49-62.
Morgan, D.P., 2002. Rating Banks: Risk and Uncertainty in an Opaque Industry, *American Economic Review* 92(4), 874-888.
Nofsinger, J. and R.W. Sias, 1999. Herding and Feedback Trading by Institutional and Individual Investors, *Journal of Finance* 54(6), 2263-2295.
Olivares, J.A., 2005. Investment Behavior of the Chilean Pension Funds. Financial Management Association European Conference Paper 360419.
Opazo, L., Raddatz, C., and S. Schmukler, 2009. The Long and the Short of Emerging Market Debt. World Bank Policy Research Working Paper 5056.
Piñera, J., 1991. El Cascabel al Gato: La Batalla por la Reforma Previsional, ed. Zig-Zag, Santiago, Chile.
Raddatz, C. and S. Schmukler, 2008. Pension Funds and Capital Market Development: How Much Bang for the Buck? World Bank Policy Research Working Paper 4787.
Reisen, H., 2000. Pensions, Savings and Capital Flows: From Ageing to Emerging Markets, Edward Elgar Publishing, Cheltenham, UK.
Scharfstein, D.S. and J.C. Stein, 1990. Herd Behavior and Investment, *American Economic Review* 80(3), 465-479.
Shiller, R.J. and J. Pound, 1989. Survey Evidence on Diffusion of Interest and Information Among Investors, *Journal of Economic Behavior and Organization* 12(1), 47-66.
Shleifer, A. and R. Vishny, 1990. Equilibrium Short Horizons of Investors and Firms, *American Economic Review* 80(2), 148-153.
Sias, R.W., 2004. Institutional Herding**,** *Review of Financial Studies 17*(1), 165-206.
Sias, R.W., 2007. Reconcilable Differences: Momentum Trading by Institutions, *Financial Review* 42(1), 1-22.
Sias, R.W. and L. Starks, 1997. Return Autocorrelation and Institutional Investors, *Journal of Financial Economics* 46(1), 103-131.
Stein, J., 2003. Agency, Information, and Corporate Investment, in: Constantinides, G., M. Harris, and R. Stulz (Eds.), Handbook of the Economics of Finance, 115-165, Elsevier, Amsterdam, North-Holland.
Stein, J., 2005. Why Are Most Funds Open-End? Competition and the Limits of Arbitrage, *Quarterly Journal of Economics* 120(1), 247-272.
The Economist, 2008. Money for Old Hope. Special Report on Asset Management, March 1.
Vittas, D., 1995. Sequencing Social Security, Pension, and Insurance Reform, World Bank Research Working Paper 1551.
Vittas, D., 1999. Pension Reform and Financial Markets, Harvard Institute for International Development, Development Discussion Paper 697.
Voronkova, S. and M. Bohl, 2005. Institutional Traders' Behavior in an Emerging Stock Market: Empirical Evidence on Polish Pension Fund Investors, *Journal of Business Finance & Accounting* 32(7-8), 1537-1560.
Wermers, R., 1999. Mutual Fund Herding and the Impact on Stock Prices, *Journal of Finance* 54(2), 581-622.

Yermo, J., 2005. The Contribution of Pension Funds to Capital Market Development in Chile, Oxford University and OECD, mimeo.
Zurita, F., 1999. Are Pension Funds Myopic? *Revista de Administración y Economía* 39, 13-15, Catholic University of Chile.

Figure 1

Pension System Holdings

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). The fund types reflect different risk profiles, from the riskiest fund (Fund A) to the most conservative fund (Fund E). The nominal values are computed for December of each year, scaled by GDP.

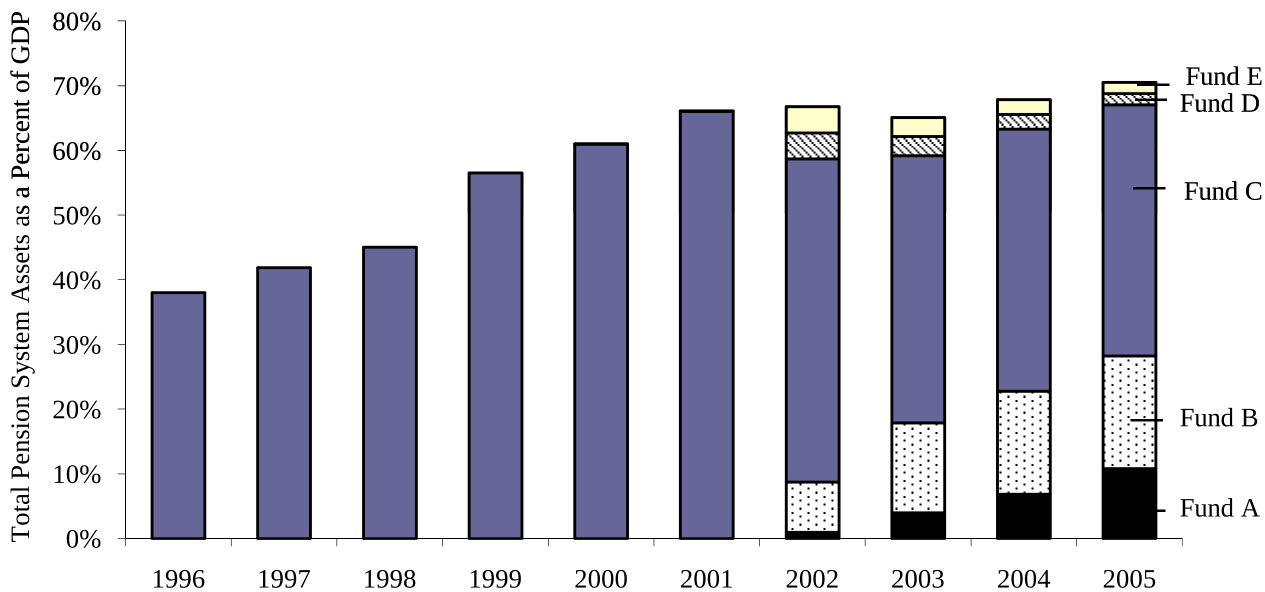

Table 1
PFA Holdings by Asset Class and Fund Type

This table presents the average share across PFAs and time of each asset class by fund type (July 1996 to December 2005 for Fund C, May 2000 to December 2005 for Fund E, September 2002 to December 2005 for Funds A, B, and D). Shares are calculated only considering asset classes shown in the table. Derivatives, investment and mutual funds quotas, former pension system bonds, deposits, and foreign assets are excluded from the analysis. Portfolio weights of each asset class are calculated per PFA and fund type, for each month, and averaged over time. For Fund E, no investments are allowed in equity.

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					
Corporate Bonds	4.6%	9.5%	9.1%	13.2%	12.3%
Financial Institutions Bonds	1.3%	2.9%	3.4%	3.3%	3.4%
Government Bonds	14.1%	29.4%	43.3%	47.9%	61.6%
Mortgage Bonds	5.2%	13.6%	19.8%	19.0%	24.0%
Equity	74.8%	44.6%	24.3%	16.6%	-

Table 2
Evolution of Chilean Equity and Fixed Income Markets

This table shows the evolution of the issuances and turnover of Chilean equity and fixed income markets from 2002 to 2005. Panel A presents the total amount issued, the number of companies, and the median amount issued by company during each year for corporate bonds, government bonds, and equity. Panel B presents the turnover ratio for each asset class as the annual value traded divided by end of the year market value. The turnover ratio for government and corporate bonds is obtained from Eterovic et al. (2011). The turnover ratio for equity is obtained from the World Development Indicators and it is adjusted by free float market capitalization using Dahlquist et al. (2003). The corporate bonds category in Panels A and B includes both financial institutions bonds and corporate bonds. Panel C presents the trading frequency for each asset class as the average percentage of trading days in which instruments are traded. Panel D presents the median amount of assets for the main companies, considering the 40 listed companies that compose the main Chilean stock market index (IPSA) for equity, and the biggest 40 companies that have outstanding corporate bonds.

Panel A. Issuances

		2002	2003	2004	2005
Corporate Bonds					
Total Amount Issued	(Millions of Dollars)	6,064	7,693	11,206	11,560
Number of Companies		36	40	54	53
Median Amount per Company	(Millions of Dollars)	95.0	114.1	150.0	175.3
Government Bonds					
Total Amount Issued	(Millions of Dollars)	2,087	4,238	4,981	4,967
Number of Issuances		80	232	263	294
Median Amount per Issue	(Millions of Dollars)	4.0	2.4	4.0	5.0
Equity					
Total Amount Issued	(Millions of Dollars)	318	44	654	1,126
Number of Companies		14	2	4	7
Median Amount per Company	(Millions of Dollars)	2.6	22.0	165.1	155.0

Panel B. Turnover Ratio

	2002	2003	2004	2005
Corporate Bonds	32%	34%	38%	40%
Government Bonds		420%	460%	290%
Equity	38%	52%	62%	76%

Panel C. Trading Frequency (Percentage of Trading Days)

	2002	2003	2004	2005
Corporate Bonds	-	-	46%	-
Government Bonds	-	-	100%	-
Equity	92%	90%	92%	95%

Panel D. Size of Main Companies Issuing Equity and Corporate Bonds (Millions of Dollars)

	2002	2003	2004	2005
Corporate Bonds	1,008	1,118	1,110	1,696
Equity	979	998	1,367	1,888

Table 3
Pension Fund Trading Activity Measures

Panel A presents trading statistics using data from the multi-fund period (2002 to 2005). Column (1) presents the average percentage of assets traded by PFAs as a share of the total number of assets held in their portfolios. Column (2) presents the average across PFAs of the difference in weights (contemporaneous weights minus lagged weights using lagged prices for both) for the traded portfolio, calculated at the PFA level. Columns (3) presents the average percentage of assets traded by funds, as a share of the total number of assets held in their portfolios. Column (4) reports the average across funds of the difference in weights for the traded portfolio, calculated at the PFA-fund level. Panel B presents the average proportion of units of a given security that a PFA incorporates into its portfolio in its first purchase and 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 and are calculated at the PFA level and the PFA-fund level, across all instruments for each asset class and averaged across PFAs or PFA-Funds. For both ratios, average and standard deviation are presented for each asset class.

Panel A. Average Percentage of Assets Traded by PFAs

	Trading Statistics			
	PFA Level		PFA-Fund Level	
	Percentage of Assets Traded Relative to Assets Held	Share of Traded Portfolio	Percentage of Assets Traded Relative to Assets Held	Share of Traded Portfolio
	(1)	(2)	(3)	(4)
All Asset Classes	15.6%	3.4%	17.4%	3.7%
Corporate Bonds	12.8%	0.2%	13.3%	0.3%
Financial Institutions Bonds	11.4%	0.1%	12.6%	0.1%
Government Bonds	12.4%	1.7%	13.6%	1.7%
Mortgage Bonds	16.2%	0.3%	18.0%	0.4%
Equity	41.9%	1.1%	35.8%	1.3%

Panel B. Proportion of Fixed-Income Instruments Bought and Held Until Expiration

	PFA Level				PFA-Fund Level			
	Ratio of Units at First Purchase to Maximum Units in Portfolio		Ratio of Units at Expiration to Maximum Units in Portfolio		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	Average	Standard Deviation	Average	Standard Deviation
PFA level	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Corporate Bonds	0.91	0.13	0.91	0.09	0.87	0.14	0.87	0.17
Financial Institutions Bonds	0.90	0.10	0.94	0.04	0.87	0.13	0.90	0.10
Government Bonds	0.66	0.23	0.85	0.10	0.61	0.21	0.89	0.07
Mortgage Bonds	0.86	0.03	0.68	0.12	0.84	0.10	0.71	0.13

Table 4

Herding at the PFA Level

This table presents the average Lakonishok et al. (1992) herding statistic by asset class at the PFA level considering each PFA as an individual entity. The herding statistic is calculated using the asset-specific probability of buying an asset at any point in time. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one, more than two, and more than three PFAs respectively. Numbers represent percentages (results are multiplied by 100). Column (4) presents the average asset-specific probability of buying an asset, calculated over the assets traded by more than one PFA, by asset class. T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic			
	Assets Traded by More than One PFA	Assets Traded by More than Two PFAs	Assets Traded by More than Three PFAs	Average Probability of Buying an Asset
	(1)	(2)	(3)	(4)
All Asset Classes	0.90 ***	2.41 ***	3.84 ***	49.05%
	(0.29)	(0.41)	(0.47)	
Domestic Assets				
Corporate Bonds	3.10 ***	10.24 ***	13.78 ***	51.61%
	(0.64)	(0.92)	(0.06)	
Financial Institutions Bonds	6.16 ***	10.31 ***	9.21 ***	51.27%
	(0.92)	(1.38)	(1.81)	
Government Bonds	-2.11	0.79 ***	3.82 ***	64.58%
	(0.16)	(0.25)	(0.46)	
Mortgage Bonds	4.58 ***	2.21 ***	1.20 ***	12.66%
	(0.07)	(0.06)	(0.06)	
Equity	1.46 ***	1.94 ***	2.44 ***	53.44%
	(0.24)	(0.27)	(0.32)	

Table 5

Herding at the PFA Level - Multi-Fund Period

This table presents the average Lakonishok et al. (1992) herding statistic by asset class at the PFA level, using data only from the multi-fund period (2002 to 2005). Each PFA is considered like an individual entity. The herding statistic is calculated using the asset-specific probability of buying an asset at any point in time. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one, more than two, and more than three PFAs respectively. Numbers represent percentages (results are multiplied by 100). Column (4) presents the average asset-specific probability of buying an asset, calculated over the assets traded by more than one PFA, by asset class. T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic			
	Assets Traded by More than One PFA	Assets Traded by More than Two PFAs	Assets Traded by More than Three PFAs	Average Probability of Buying an Asset
	(1)	(2)	(3)	(4)
All Asset Classes	-1.01	2.00 ***	4.02 ***	45.65%
	(0.47)	(0.71)	(0.77)	
Domestic Assets				
Corporate Bonds	1.65 **	12.52 ***	20.55 ***	51.32%
	(0.79)	(1.33)	(0.06)	
Financial Institutions Bonds	7.49 ***	13.17 ***	11.46 ***	33.21%
	(1.18)	(1.77)	(2.48)	
Government Bonds	-5.06	-0.83	1.88 **	55.44%
	(0.29)	(0.44)	(0.86)	
Mortgage Bonds	1.06 ***	-0.63	-0.81	3.94%
	(0.08)	(0.05)	(0.05)	
Equity	0.34	0.42	0.49	57.54%
	(0.41)	(0.43)	(0.50)	

Table 6

Herding at the PFA-Fund Level

This table presents the average Lakonishok et al. (1992) herding statistic by asset class at the PFA-fund level, using data from the multi-fund period (2002 to 2005). Each fund in each PFA is considered like an individual entity. The herding statistic is calculated using the asset-specific probability of buying an asset at any point in time. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one, more than two, and more than three funds respectively. Numbers represent percentages (results are multiplied by 100). Column (4) presents the average asset-specific probability of buying an asset, calculated over the assets traded by more than one fund, by asset class. T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic			Average Probability of Buying an Asset
	Assets Traded by More than One Fund	Assets Traded by More than Two Funds	Assets Traded by More than Three Funds	
	(1)	(2)	(3)	(4)
All Asset Classes	-1.46	0.63 *	1.48 ***	52.83%
	(0.31)	(0.37)	(0.36)	
Domestic Assets				
Corporate Bonds	-0.96	2.46 ***	4.58 ***	54.95%
	(0.47)	(0.58)	(0.07)	
Financial Institutions Bonds	1.42 **	6.09 ***	8.37 ***	43.97%
	(0.76)	(1.03)	(1.23)	
Government Bonds	-4.56	-0.97	0.22	57.65%
	(0.19)	(0.25)	(0.32)	
Mortgage Bonds	0.18 **	-0.17	-0.11	9.29%
	(0.08)	(0.07)	(0.07)	
Equity	0.50 **	1.15 ***	1.33 ***	54.44%
	(0.29)	(0.28)	(0.29)	

Table 7

Herding within PFAs across Funds

This table presents the average Lakonishok et al. (1992) herding statistic by asset class, using data from the multi-fund period (2002 to 2005). The herding statistic is calculated within PFAs and across funds and then averaged across PFAs, using the asset-specific probability of buying an asset at any point in time. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one, more than two, and more than three funds respectively. Numbers represent percentages (results are multiplied by 100). Column (4) presents the average asset-specific probability of buying an asset, calculated over the assets traded by more than one fund, by asset class. T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic			
	Assets Traded by More than One Fund	Assets Traded by More than Two Funds	Assets Traded by More than Three Funds	Average Probability of Buying an Asset
	(1)	(2)	(3)	(4)
All Asset Classes	-2.15	2.49 ***	5.36 ***	48.77%
	(0.47)	(0.69)	(0.84)	
Domestic Assets				
Corporate Bonds	-0.62	5.84 ***	11.85 ***	58.15%
	(0.71)	(1.01)	(0.24)	
Financial Institutions Bonds	0.27	8.63 ***	12.38 ***	44.77%
	(0.97)	(1.38)	(1.85)	
Government Bonds	-3.26	4.87 ***	9.28 ***	56.32%
	(0.38)	(0.68)	(1.03)	
Mortgage Bonds	-2.93	-0.83	1.22 ***	10.35%
	(0.10)	(0.12)	(0.25)	
Equity	-1.39	-1.03	-1.25	58.16%
	(0.45)	(0.54)	(0.76)	

Table 8

Herding within Fund Types across PFAs

This table presents the average Lakonishok et al. (1992) herding statistic by asset class, using data from the multi-fund period (2002 to 2005). The herding statistic is calculated within fund type and across PFAs and then averaged across funds, using the asset-specific probability of buying an asset at any point in time. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one, more than two, and more than three funds respectively. Numbers represent percentages (results are multiplied by 100). Column (4) presents the average asset-specific probability of buying an asset, calculated over the assets traded by more than one fund, by asset class. T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic			
	Assets Traded by More than One Fund	Assets Traded by More than Two Funds	Assets Traded by More than Three Funds	Average Probability of Buying an Asset
	(1)	(2)	(3)	(4)
All Asset Classes	3.71 ***	5.22 ***	5.80 ***	48.44%
	(0.39)	(0.59)	(0.94)	
Domestic Assets				
Corporate Bonds	12.33 ***	19.57 ***	24.03 ***	52.73%
	(0.68)	(0.85)	(0.10)	
Financial Institutions Bonds	12.51 ***	15.49 ***	14.47 ***	37.53%
	(1.01)	(1.51)	(2.62)	
Government Bonds	1.20 ***	3.43 ***	3.10 ***	57.94%
	(0.35)	(0.67)	(1.18)	
Mortgage Bonds	1.93 ***	0.21 ***	-0.10	4.66%
	(0.08)	(0.07)	(0.08)	
Equity	5.20 ***	5.88 ***	7.54 ***	54.79%
	(0.32)	(0.35)	(0.43)	

Table 9

Herding within Fund Types Across PFAs, by Fund Type

This table presents the average Lakonishok et al. (1992) herding statistic by asset class, using data from the multi-fund period (2002 to 2005). The herding statistic is calculated within fundtypes and across funds (one per PFA), by fund type, considering assets traded by more than one fund for each fund type. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Numbers represent percentages (results are multiplied by 100). For Fund E no investments are allowed in equity. T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic - Assets Traded by More than One Fund				
	Fund A	Fund B	Fund C	Fund D	Fund E
	(1)	(2)	(3)	(4)	(5)
All Asset Classes	5.87 ***	3.54 ***	7.99 ***	5.65 ***	4.67 ***
	(0.92)	(0.65)	(0.49)	(0.66)	(0.84)
Domestic Assets					
Corporate Bonds	13.61 ***	11.47 ***	20.80 ***	10.51 ***	13.02 ***
	(1.93)	(0.85)	(0.08)	(0.88)	(1.06)
Financial Institutions Bonds	6.63 ***	10.78 ***	15.33 ***	9.49 ***	13.56 ***
	(2.61)	(1.29)	(1.21)	(1.25)	(1.70)
Government Bonds	1.21	4.91 ***	2.96 ***	4.94 ***	2.08 ***
	(1.72)	(0.84)	(0.44)	(0.67)	(0.80)
Mortgage Bonds	5.02 ***	2.89 ***	1.24 ***	2.52 ***	3.26 ***
	(0.85)	(0.17)	(0.08)	(0.14)	(0.32)
Equity	6.32 ***	0.69 *	10.43 ***	6.68 ***	-
	(0.43)	(0.45)	(0.60)	(0.64)	-

Table 10

Herding at PFA Level, Excluding Purchases at Issuance

This table presents the average Lakonishok et al. (1992) herding statistic by asset class at the PFA level considering each PFA as an individual entity. First purchases are excluded for fixed income categories in order to distinguish herding at the issuance date. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one, more than two, and more than three PFAs respectively. Numbers represent percentages (results are multiplied by 100). Column (4) presents the average asset-specific probability of buying an asset, calculated over the assets traded by more than one PFA, by asset class. T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic			
	Assets Traded by More than One PFA	Assets Traded by More than Two PFAs	Assets Traded by More than Three PFAs	Average Probability of Buying an Asset
	(1)	(2)	(3)	(4)
All Asset Classes	-0.58	0.32	1.37 ***	41.95%
	(0.28)	(0.41)	(0.43)	
Domestic Assets				
Corporate Bonds	1.58	3.19 ***	6.97 ***	36.04%
	(0.61)	(1.02)	(0.05)	
Financial Institutions Bonds	1.09	2.45 **	2.32 *	18.87%
	(0.91)	(1.06)	(1.17)	
Government Bonds	-3.97	-1.57	0.20	56.56%
	(0.17)	(0.27)	(0.53)	
Mortgage Bonds	2.66 ***	0.80 ***	0.28 ***	4.19%
	(0.06)	(0.05)	(0.05)	
Equity	1.46 ***	1.94 ***	2.44 ***	54.79%
	(0.24)	(0.27)	(0.32)	

Table 11

Herding within Fund Types across PFAs, Excluding Purchases at Issuance

This table presents the average Lakonishok et al. (1992) herding statistic by asset class, using data from the multi-fund period (2002 to 2005). First purchases are excluded for fixed income categories in order to distinguish herding at the issuance date. The herding statistic is calculated within fund type and across PFAs and then averaged across funds. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one, more than two, and more than three funds, respectively. Numbers represent percentages (results are multiplied by 100). Column (4) presents the average asset-specific probability of buying an asset, calculated over the assets traded by more than one fund, by asset class. T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic			
	Assets Traded by More than One Fund	Assets Traded by More than Two Funds	Assets Traded by More than Three Funds	Average Probability of Buying an Asset
	(1)	(2)	(3)	(4)
All Asset Classes	2.99 ***	4.16 ***	4.43 ***	45.94%
	(0.37)	(0.59)	(0.94)	
Domestic Assets				
Corporate Bonds	11.58 ***	17.32 ***	21.61 ***	36.04%
	(0.70)	(0.92)	(0.10)	
Financial Institutions Bonds	7.79 ***	8.93 ***	6.27 **	18.87%
	(0.92)	(1.42)	(2.69)	
Government Bonds	0.83 **	2.88 ***	2.37 **	56.56%
	(0.36)	(0.67)	(1.19)	
Mortgage Bonds	1.67 ***	0.37 ***	0.06	4.19%
	(0.07)	(0.06)	(0.08)	
Equity	5.20 ***	5.88 ***	7.54 ***	54.79%
	(0.32)	(0.35)	(0.43)	

Table 12

Buy and Sell Herding at PFA Level

This table presents the total average Lakonishok et al. (1992) herding statistic at the PFA level and the statistic for buys and sells subgroups following Grinblatt et al. (1995) methodology. Each PFA is considered like an individual entity and the herding statistic is calculated using the asset-specific probability of buying an asset at any point in time. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one PFA, columns (4), (5), and (6) present the results for asstes traded by more than two PFAs, and columns (7), (8), and (9) the results for more than three PFAs. Numbers represent percentages (results are multiplied by 100). T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic								
	Assets Traded by More than One PFA			Assets Traded by More than Two PFAs			Assets Traded by More than Three PFAs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Buys	Sells	Total	Buys	Sells	Total	Buys	Sells
All Asset Classes	0.90 ***	8.85 ***	-1.27	2.41 ***	7.84 ***	2.56 ***	3.84 ***	8.58 ***	3.02 ***
	(0.29)	(0.50)	(0.33)	(0.41)	(0.76)	(0.50)	(0.57)	(1.15)	(0.77)
Domestic Assets									
Corporate Bonds	3.1 ***	1.9 **	6.08 ***	10.24 ***	11.07 ***	12.34 ***	13.78 ***	13.73 ***	19.01 ***
	(0.64)	(0.92)	(0.03)	(0.92)	(1.36)	(0.02)	(1.18)	(1.73)	(0.03)
Financial Institutions Bonds	6.16 ***	13.07 ***	5.38 ***	10.31 ***	20.04 ***	11.76 ***	9.21 ***	22.4 ***	9.69 ***
	(0.92)	(2.08)	(1.32)	(1.38)	(3.27)	(2.00)	(1.81)	(5.41)	(2.25)
Government Bonds	-2.05	0.93 ***	-4.41	0.76 ***	-0.15	2.06 ***	3.78 ***	4.8 ***	2.02 **
	(0.16)	(0.17)	(0.24)	(0.25)	(0.29)	(0.45)	(0.46)	(0.48)	(0.94)
Mortgage Bonds	4.58 ***	34.41 ***	-1.87	2.21 ***	27.89 ***	-1.24	1.2 ***	19.16 ***	-0.96
	(0.07)	(0.27)	(0.01)	(0.06)	(0.40)	(0.01)	(0.06)	(0.47)	(0.02)
Equity	1.46 ***	1.62 ***	1.47 ***	1.94 ***	1.41 ***	2.58 ***	2.44 ***	2.52 ***	2.42 ***
	(0.24)	(0.33)	(0.36)	(0.27)	(0.36)	(0.41)	(0.32)	(0.42)	(0.50)

Table 13

Buy and Sell Herding within Fund Types across PFAs

This table presents the total average Lakonishok et al. (1992) herding statistic and the statistic for buys and sells subgroups following Grinblatt et al. (1995) methodology, using only data from the multi-fund period (2002 to 2005). The herding statistic is calculated within fund type and across PFAs, and then averaged across funds, using the asset-specific probability of buying an asset at any point in time. The herding statistic over all asset classes is calculated based on the average portfolio share of each asset class. Columns (1), (2), and (3) present the results considering assets traded by more than one PFA, columns (4), (5), and (6) present the results for asstes traded by more than two PFAs, and columns (7), (8), and (9) the results for more than three PFAs. Numbers represent percentages (results are multiplied by 100). T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic								
	Assets Traded by More than One Fund			Assets Traded by More than Two Funds			Assets Traded by More than Three Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Buys	Sells	Total	Buys	Sells	Total	Buys	Sells
All Asset Classes	3.71 ***	5.88 ***	2.01 ***	5.22 ***	8.85 ***	5.60 ***	5.80 ***	9.97 ***	4.74 ***
	(0.29)	(0.50)	(0.33)	(0.41)	(0.76)	(0.50)	(0.57)	(1.15)	(0.77)
Domestic Assets									
Corporate Bonds	12.33 ***	11.65 ***	15.01 ***	19.57 ***	16.14 ***	22.54 ***	24.03 ***	20.30 ***	26.80 ***
	(0.68)	(0.76)	(0.04)	(0.85)	(1.36)	(0.05)	(1.02)	(1.64)	(0.08)
Financial Institutions Bonds	12.51 ***	14.34 ***	12.18 ***	15.49 ***	17.57 ***	18.63 ***	14.47 ***	19.81 ***	18.38 ***
	(1.01)	(1.29)	(1.99)	(1.51)	(2.51)	(2.15)	(2.62)	(5.28)	(3.70)
Government Bonds	1.20 ***	1.19 ***	1.22 **	3.43 ***	0.28	6.24 ***	3.10 ***	3.26 ***	2.96 *
	(0.35)	(0.41)	(0.70)	(0.67)	(0.88)	(0.98)	(1.18)	(1.36)	(1.93)
Mortgage Bonds	1.93 ***	10.73 ***	-0.81	0.21 ***	24.91 ***	-0.94	-0.10	19.25 ***	-1.07
	(0.08)	(0.31)	(0.03)	(0.07)	(0.82)	(0.04)	(0.08)	(0.83)	(0.05)
Equity	5.20 ***	6.69 ***	0.47	5.88 ***	7.19 ***	2.42 ***	7.54 ***	8.92 ***	3.64 ***
	(0.32)	(0.33)	(0.77)	(0.35)	(0.39)	(0.75)	(0.43)	(0.47)	(0.91)

Table 14

Dynamic Herding by Fund Type

This table presents a measure of dynamic herding across time for all assets and by asset class, for each fund type. For each moment in time, we run an ordinary least squares regression of the probability of buying an instrument at that moment on the lagged probability of buying an instrument. The average coefficient of this exercise is shown in the table. Numbers represent percentages (results are multiplied by 100). T-tests are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The standard errors of the average coefficient are presented in parentheses. In addition, this table presents the percentage of positive and negative coefficients that are statistically significant at a 10% level. The dashes in column (5) indicate that equity is not traded by Fund E.

		Herding Regressions. All Assets				
		Fund A	Fund B	Fund C	Fund D	Fund E
		(1)	(2)	(3)	(4)	(5)
All Asset Classes	Average Coefficient	-15.49 ***	-32.75 ***	-28.12 ***	-29.59 ***	-41.08 ***
	Standard Error	(2.06)	(2.82)	(2.70)	(2.69)	(3.21)
	% of Positive Coefficients	0.00 %	0.00 %	10.53 %	0.00 %	0.00 %
	% of Negative Coefficients	59.46 %	91.89 %	86.84 %	91.89 %	92.11 %
Domestic Assets						
Corporate Bonds	Average Coefficient	-15.33	-21.38 **	-20.90 ***	-3.23	-10.82
	Standard Error	(10.7)	(7.75)	(3.93)	(5.69)	(6.65)
	% of Positive Coefficients	0.00 %	0.00 %	0.00 %	0.00 %	3.03 %
	% of Negative Coefficients	12.50 %	12.50 %	20.00 %	85.71 %	12.12 %
Financial Institutions Bonds	Average Coefficient	-29.47	-19.95	-9.58	-31.11 *	-22.74
	Standard Error	(40.9)	(25.9)	(12.8)	(16.1)	(20.5)
	% of Positive Coefficients	0.00 %	0.00 %	12.50 %	0.00 %	0.00 %
	% of Negative Coefficients	0.00 %	0.00 %	12.50 %	0.00 %	0.00 %
Government Bonds	Average Coefficient	-33.95 ***	-36.56 ***	-28.33 ***	-31.89 ***	-38.50 ***
	Standard Error	(5.43)	(3.30)	(3.22)	(2.97)	(4.64)
	% of Positive Coefficients	0.00 %	0.00 %	2.63 %	0.00 %	2.63 %
	% of Negative Coefficients	34.29 %	70.27 %	73.68 %	72.97 %	73.68 %
Mortgage Bonds	Average Coefficient	-63.53 ***	-55.57 ***	-40.83 ***	-45.14 ***	-43.67 ***
	Standard Error	(6.45)	(4.44)	(3.74)	(4.14)	(4.04)
	% of Positive Coefficients	0.00 %	0.00 %	7.89 %	0.00 %	0.00 %
	% of Negative Coefficients	89.29 %	91.89 %	86.84 %	89.19 %	86.49 %
Equity	Average Coefficient	17.79 ***	21.73 ***	22.42 ***	0.65	-
	Standard Error	(2.67)	(4.00)	(3.34)	(4.79)	-
	% of Positive Coefficients	56.76 %	45.95 %	57.89 %	21.21 %	-
	% of Negative Coefficients	2.70 %	0.00 %	2.63 %	6.06 %	-

Table 15

Does Momentum Explain Herding?

This table presents the results of ordinary least squares regression of the herding statistic that uses the asset-specific probability of buying an asset, on a constant and the lagged rate of return. The regressions are computed over all asset classes and for each asset class separately, considering assets traded by more than two PFAs or funds. Numbers represent percentages (results are multiplied by 100). T-tests are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

	Herding Statistic on Lagged Return							
	PFA Level		PFA Level (Multi-Fund Period)		PFA-Fund Level		Within Fund Types across PFAs	
	Constant	Lagged Return	Constant	Lagged Return	Constant	Lagged Return	Constant	Lagged Return
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All Asset Classes	0.85 ***	-5.79 *	-0.69	0.94	-0.48	-0.98	1.04 ***	10.64
	(0.02)	(3.72)	(0.02)	(3.29)	(0.02)	(4.02)	(0.06)	(7.11)
Domestic Assets								
Corporate Bonds	8.54 ***	47.53	8.69 ***	87.42	-0.11	-8.09	19.89 ***	15.54
	(0.20)	(88.22)	(0.07)	(97.59)	(0.00)	(13.95)	(0.03)	(21.45)
Financial Institutions Bonds	8.12 ***	-82.76 **	8.69 ***	-84.08 **	2.87 ***	-35.90	12.49 ***	-29.25 **
	(0.15)	(47.14)	(0.05)	(45.72)	(0.08)	(33.74)	(0.05)	(12.56)
Government Bonds	-1.67	12.38	-2.26	8.66	-2.52	15.7 ***	5.38 ***	8.67
	(0.08)	(18.74)	(0.02)	(15.11)	(0.02)	(4.69)	(0.00)	(11.69)
Mortgage Bonds	1.21 ***	-44.8 ***	-0.64 *	-17.33 *	-0.53	-12.60	0.17 ***	-9.02
	(0.13)	(16.18)	(0.08)	(11.58)	(0.06)	(12.34)	(0.05)	(7.55)
Equity	1.68 ***	-3.45	0.06	6.61	0.87 ***	2.70	6.48 ***	0.58
	(0.02)	(4.03)	(0.10)	(5.26)	(0.06)	(2.71)	(0.10)	(4.88)

Table 16

Evolution of Herding Statistic

This table presents the average Lakonishok et al. (1992) herding statistic by asset class considering 18 months before and after the regulatory reform in October 1999. Panel A shows the herding statistic for Fund C, using the asset-specific probability of buying an asset at any point in time. Numbers represent percentages (results are multiplied by 100). Panel B shows p-values for the one-sided t-test of equality of the herding statistic between the observations previous to the regulatory reform (April 1998 to October 1999) and the observations after the reform (October 1999 to April 2001). T-tests are one-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are presented in parentheses.

Panel A. Herding Statistic

	Assets Traded by More than One PFA		Assets Traded by More than Two PFAs		Assets Traded by More than Three PFAs	
	Before Regulatory Reform	After Regulatory Reform	Before Regulatory Reform	After Regulatory Reform	Before Regulatory Reform	After Regulatory Reform
Corporate Bonds	4.15 **	7.07 ***	2.19 **	8.85 ***	1.85 **	8.29 ***
	(1.81)	(1.94)	(0.98)	(2.38)	(0.90)	(2.85)
Financial Institutions Bonds	-0.57	7.01 **	-0.43	8.03 **	7.61	6.47 **
	(2.22)	(3.13)	(2.96)	(4.16)	(4.03)	(2.32)
Government Bonds	-0.44	-0.00	1.10	0.79 **	3.40 **	2.30 ***
	(0.44)	(0.27)	(0.87)	(0.46)	(1.44)	(0.87)
Mortgage Bonds	6.56 ***	6.02 ***	3.46 ***	2.65 ***	1.70 ***	1.10 ***
	(0.21)	(0.20)	(0.19)	(0.18)	(0.17)	(0.16)
Equity	0.81 *	2.64 ***	1.16 **	3.15 ***	1.60 **	4.14 ***
	(0.61)	(0.68)	(0.70)	(0.79)	(0.83)	(0.96)

Panel B. P-Value for Hypothesis Testing: Herding Before the Reform > Herding After the Reform

	Assets Traded by More than One PFA	Assets Traded by More than Two PFAs	Assets Traded by More than Three PFAs
Corporate Bonds	0.93	1.00	0.99
Financial Institutions Bonds	0.98	0.95	0.40
Government Bonds	0.79	0.40	0.28
Mortgage Bonds	0.01	0.00	0.00
Equity	0.98	0.98	0.99