GHULAME RUBBANIY

Investment Behavior of Institutional Investors

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Investeringsgedrag van institutionele beleggers

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Ghulame Rubbaniy

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ERASMUS UNIVERSITEIT ROTTERDAM

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Ghulame Rubbaniy

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Chapter 1: Aims and Scope

1.1. Introduction

What the determinants of institutional investment behavior are and how these determinants can affect the portfolio choice of institutional investors, has been a heated debate among academics, policy makers and professionals in the last decades. Sometimes institutional investment behavior can be explained by financial theory, for instance the efficient market hypothesis and CAPM. At some other times however, financial literature does not provide convincing explanation for determinants of institutional asset allocation decisions examples are for instance calendar anomalies and home bias. The determinants of institutional investment behavior may vary due to investment horizon of institutional investors, for instance long-term or short-term, on account of the risk preferences of the institutional investors, for instance pension funds (PFs), mutual funds (MFs) and hedge funds or owing to the prevailing regulatory environment, for instance capital mobility restrictions across countries as well as institutional investors. These determinants of investment behavior across institutional investors are the focus of this dissertation.

Institutional investors vary on the basis of their investment horizon. In general, PFs are considered to be long-term investors while MFs and hedge funds are believed to have short-term investment horizon. The investment horizon can affect their strategic asset mix as the short-term investors, in contrast to long-term traders, may face an urgency to quickly adjust their portfolios out of liquidity needs or return chase; wherein the determinants of institutional investment behavior may differ based on the investment horizon. In terms of risk preferences, hedge funds capture the top and PFs fall to the bottom of the list of institutional investors while developing their strategic asset allocation plans. MFs are more considered to be riskier than PFs and conservative than hedge funds considering the risk taking ability of the institutional investors in terms of asset allocation. Their risk preference may suggest different determinants of their investment behavior. For instance, PFs are risk-averse investors holding relatively less-risky and less-liquid long-term exposures depending upon their pension pay out policy. On the other hand MFs who are usually more interested in short-term investments and more risky liquid assets in pursuit of higher returns and liquidity needs. Regulatory restrictions may vary at macro level for these institutions across countries and at micro level across institutional investors. The US is considered to be highly regulated compared to Europe whereas PFs are more prudentially supervised in comparison with MFs and hedge funds. For instance, in US existence of Pension Benefit Guarantee Corporation protects the PFs defaults and may encourage PFs to hold more risky positions compare to the Netherlands where the risk of default lies with the sponsor and conservative asset allocation decisions are required. These varying regulatory conditions across institutional investors appear to affect their portfolio choice decisions; for instance, a MF could be interested in growth oriented stocks while a PF might have chosen to invest in a passive index.

Financial literature presents a great deal of studies shedding light on determinants of investment behavior of the institutional investors [Lakonishok et al. (1992), Grinblatt et al. (1995), Sias (1999), Wermers(2002)]; this popular press is mainly limited to US institutional investors or constrained by the data availability in other countries. Even the same data across countries changes the determinants of institutional investment behavior due to the prevailed regulatory environment across countries. Institutional trading behavior may also subject to time span for which the data is available i.e. availability of more refined, high frequency, data over time may provide more insights to confirm (reject) the existing theories about these determinants. For instance, herding is found to be more pronounced in high frequency data, while it is less dominant in times of financial turmoil. In a similar fashion, home bias could be higher in times of distress or vice versa.

This study provides an empirical analysis of the investment behavior of the institutional investors across two countries and institutional investors. We examine the portfolio choice anomalies and trading strategies of two types of institutional investors in our study, Dutch PFs and US MFs, and present some explanation for the unexpected behavior in their trading. Particularly we focus on the determinants of home bias, feedback trading and herding in the investment behavior of these institutional investors. Given the importance of institutional investment behavior to government, policymakers, investors, economists, academics and practitioners, we explore the potential explanations for these determinants concentrating on investors' characteristics, properties of the asset classes, market conditions and investors' trading strategies across markets.

Financial premises discern two main types of investors operating in the financial world: (1) followers of efficient market hypothesis (EMH) and (2) proponents of markets inefficiencies. The advocates of EMH believe that financial markets are information efficient and current asset prices contain all the information such that the future stock prices are unpredictable [Fama (1970)]. On the other hand, critics of the EMH claim that financial markets are inefficient and document the stock prices to be predictable [Carhart(2012)]. For instance, in efficient markets abnormal returns cannot be earned consistently in the long-run using feedback strategies and home bias in the portfolio choice of the international investors should not be significant. EMH has been popular for quite a while but a parallel approach of Sharpe (2012) and Linter (1965) developed the traditional portfolio theory which helped to provide the foundation for the, most commonly used, capital asset pricing model (CAPM). With the advent of the CAPM the idea of market inefficiencies and their exploitation to earn abnormal returns got stronger; especially, weak from of EMH came under serious criticism. Some studies [William Sharpe (2012)] provide strong evidence that market inefficiencies lead financial experts to start believing that stock returns are predictable; the idea of mean-variance also portfolio came to the fore to improve capital asset allocation efficiency. Furthermore, efficient and optimal mean-variance portfolio and use of CAPM has become popular for both the investors and portfolio managers. According to the international version of the classical capital asset pricing model (ICAPM), international investors, irrespective of their country of residence, are necessary to hold a world market portfolio of risky assets in order to maximize their risk-adjusted returns; however, the proportion of foreign assets in investors' portfolios tends to be very small in practice. Investors are found to hold a disproportionately lower share of foreign equity exposures when they consider relative stock market capitalizations [Cooper and Kaplanis (1994), Tesar and Werner (1995)]. Furthermore, gains are also evidenced from international portfolio diversification – see for instance Lewis (1999), Driessen et al. (2007). The phenomenon of holding little exposures of foreign assets relative to what is suggested by prediction of financial models is commonly known as home bias and among others French et al. (1991), Cooper et al. (1994), and Tesar et al. (1995) document this in their studies. Though it is the least controversial stylized fact in international finance [Dahlquistet,al (2003)], yet an optimal level of home bias is inconclusive in financial literature across financial markets. Different explanations of home bias have been presented in the literature to explain the home bias in the trading behavior of the (institutional) investors. They include, but not limited to, the high information cost about foreign investments [Kang and Stulz (1997)], investment preference in the familiar investment opportunities [Huberman (2001)], low visibility of the firm to foreign investors [Ahearne et al. (2004)], lower credibility of the financial information [Suh(2001)], departure from purchasing power parity [Cooper and Kaplanis (1994)], transportation costs [Obstfeld and Rogoff (2001)], transaction costs [Coeurdacier (2009)], information asymmetry [Warnock et al. (2004)] and hedging of human capital and other non-tradable assets [Stockman and Dellas. (1989)]. Given the benefits of the diversification [Lewis (1999) and Britten-Jones (2002)] we examine home bias in the investment allocation choices of institutional investors using fund characteristics as the explanations. Chapter 2 particularly explains the evolution and determinants of home bias in the portfolio choice of the Dutch PFs.

Traditionally, in context of goals, PFs are perceived to be long term investors focusing majorly on buy and hold strategies. Being long-term investor they could be more interested to invest in the long-term assets, buy and hold securities, and do not rebalance their assets quite often; however, their offered pension plans may affect their investment strategies for instance, in case of defined contribution pension plans PFs are not perceived to be profit oriented and the whole risk of investment returns lies with the employee. Nevertheless, they are risk and trading cost averse that actually drags them to passive investment. In case of defined benefit (DB) plan settings, however, employer has to provide agreed benefits to the employee at retirement, which places more investment risk to the employer shoulders and thus brings some attraction for the employer to be involved in the portfolio management of the PF. Moreover, a 50-50% participation of employer and employees' representatives in the board of directors (Dutch Pension System) may increase the possibility of this involvement. Another important factor that can affect the asset allocation decisions of the fund management is the compensation to the fund management on better performance i.e. if the PF performs well it does not only negatively affect the employer's contribution to the pension plan but also provides the rewards to the pension fund management. In this context fund management of the PFs may trade actively in pursuit of the higher returns. In fact, one study has already suggested Dutch PFs to be passive (Yu et al., 2009). This situation calls for a thorough investigation of the active trading in the Dutch PFs as the more they become active the lower the returns due to the transaction costs will be. While trading institutional investors may exhibit feedback trading and in doing so they may follow each other. This phenomenon is called herding and studies on herding posit mixed and divergent results about its existence. Some studies provide strong existence of herding in the trading behavior of institutional investors while others document modest or little herding evidence [Lakonishok et al. (1992), Grinblatt et al. (1995)]. Since Dutch PFs hold huge amount of assets and trading of same assets in the same direction at the same time, if happens, with such a big amount can affect the security prices. Alternatively, shifts to the economic conditions may also affect the trading behavior of the institutional investors e.g. in times of financial turmoils they may behave differently compared to the normal times. Our rich data set coupled with the inconclusive results on feedback trading and herding in institutional investors provides us with the opportunity to investigate a few questions about trading behavior of the institutional investors in Netherlands i.e. do they trade actively? While trading do they jump on the band wagon? Is their trading behavior affected by the macro-economic shifts for instance economic crises? Taking these questions and the existing theories about the feedback trading strategies - momentum and contrarian - and herding of the institutional investors, in to account we devote Chapter 3 of this thesis for this discussion.

In many countries institutional investors are dominating, in terms of capitalization, the markets over time; for instance in Netherlands PFs alone hold about 850 billion euro of assets, 150% of the Dutch GDP [Bikker et al. (2007)]. Similarly, in US institutions account for about 64% of the market value of the CRSP [Dasgupta et al. (2011)]. Being dominant institutional investors in US, mutual funds are holding about 4 trillion US dollars by the end of 2007 [Glode, (2011)] with an impressive growth rate of 16% over the years 1980 to 2008 [Wahal et al. (2011)]. Impressed by the enormously increasing amount of assets over time and considering the documented divergent views about herding in US mutual funds, we investigate the herding dynamics in their trading strategies and its determinants. A chronological investigation of different studies [Lakonishok et al. (1992), Grinblatt et al. (1995), Wermers (2002) and Patterson et al. (2006)] shows that herding in the institutional investors is increasing over time but literature appears to be silent to expose any study that could have investigated the evolution of herding in trading behavior of US mutual funds. Literature also documents the determinants of herding [for instance Grinblatt et al. (1995)] and the trading behavior of the MFs during different market conditions [Chao et al. (1999)]. We corroborate to the determinants of the MFs herding behavior by investigating funds styles, funds market capitalization, MFs participation to the financial markets and market realized volatility as the determinants of US mutual funds' herding. We also investigate a possible shift in their herding behavior during bad and good market times. Chapter 4 of this thesis has been reserved for this discussion.

1.2. Research Objectives

The nitty-gritty of this research revolves around the following research questions:

1. Do Dutch PFs experience home bias it their trading behavior? If yes, what are its dynamics and determinants?

2. Are Dutch PFs passive investors? While trading do they follow feedback trading? If yes, do they also herd?

3. What are the fund specific and market specific determinants of herding behavior in US mutual funds? Is this herd behavior affected by the major economic shocks?

1.3. Research Contributions

Through this research we contribute both to the Dutch (domestic) and international scientific literature in different ways. First of all, most of the financial literature that has investigated home bias takes the perspective of a US investor; home bias study outside of US is scarce and, if available, does not explain the dynamics of home bias in mature markets. The availability of multi-asset data in a mature PF industry with a sufficiently long horizon and different regulatory environment provides us the opportunity to study the cross-sectional variation in domestic bias in the portfolio choices of the Dutch institutional investors over time and across asset classes.

Secondly, in comparison to many other studies, herding behavior in Dutch PFs has been investigated using higher frequency (monthly) data that provide more insights than the quarterly data because the market's ability to absorb large trade imbalances engendered by institutional herds is more limited over shorter time horizons.[1] In addition, Dutch PFs are important in the international financial markets due to their high volume of assets; therefore, analysis of their investment behavior may help us understand the dynamics of the financial markets in which they operate. Our investigation of institutional investment behavior covers several asset classes, whereas distant studies are limited to equities only.

Thirdly, we investigate herding over time and provide empirical evidences about rampant herding in the trading behavior of US institutional investors. We focus on US mutual funds' styles, funds' market capitalization, MFs' participation to the financial markets and market realized volatility as the determinants of the rampant herding over time. We also analyze the herding behavior of MFs during both bull and bear markets conditions to see if herding in trading behavior of MFs co-move with market conditions. Finally, we extend the existing literature on characteristics herding for instance stocks sensitivity to market movements (beta).

[1] "Short-term institutional herding and impact on stock prices" by Puckett et al. (2009)

1.4. Thesis Structure

This dissertation comprises of five chapters: Chapter 2 concentrates on asset allocation dynamics of Dutch PFs with a typical focus on home bias and its fund specific determinants. The objective of Chapter 3 is to explore the passiveness in the investment behavior of the Dutch PFs. It further investigates the feedback trading decisions and the factors theses decisions hinge on. Herding behavior and its determinants in the trading of US mutual funds has been analysed in Chapter 4 of this thesis. Additionally, this chapter explains herding behavior of US mutual funds using fund specific, market specific and security specific determinants. Finally, Chapter 5 concludes and opens the channels for future research.

Chapter 2: Home Bias and Dutch PFs' Investment Behavior

Don't put all your eggs in one basket.

Using a panel data set of more than 600 Dutch pension funds (PFs) between 1992 and 2006 we investigate asset allocation behavior of Dutch PFs across multiple asset classes. We find that a domestic investment, also known as home bias, in portfolio choices of Dutch institutional investors has fallen. We also find that the introduction of the euro, thedot-com crisis (1999-2001) and individual PF´s characteristics are significant determinants of home bias. Overall, maturePFs´portfolios are diversified internationally whereas large PFs seem to prefer to only scale up their foreign, less-risky positions at the expense of domestic fixed income positions. The effect of the dot-com crisis is more pronounced for domestic bonds whereas the introduction of the euro was more important for domestic equities.

2.1. Introduction

The global integration of financial markets is providing an increasing opportunity for investors all over the world to invest abroad. Generally, this international diversification offers higher returns at a given level of risk in comparison to an internationally non-diversified portfolio (Grubel (1968), Eldor et al. (1988)). Various authors have analysed this risk return trade off from different angles. Solnik (1974) shows how portfolio risk can be reduced by investing in international stocks and hedging the associated foreign exchange-rate risks. Others have documented global portfolios as a means of substantial risk-return improvement (Grinblatt (1995)), Clarke and Tullis (1999), Michaud et al. (1996), Laster (1998)).Using mean-variance optimization in combination with the capital asset pricing model (CAPM), Black and Litterman (1992) have shown that, at a given level of risk, international diversification improves portfolio performance.

Institutional investors, like PFs, are well placed to take advantage of diversifying their investments internationally and improve their investment performance in terms of risk and return. In such a risk-return optimization setting this implies a particular allocation of investments domestically and abroad. In this context a too high proportion of domestic holdings in the portfolio choices ofinvestors is referred to as 'home bias'. It is a well-documented characteristic of the international equity portfolios and many studies have reported strong evidences for its existence e.g. (Tesarand Werner (1995) and Cooper and Kaplanis (1994)).

The literature has uncovered different explanations for home bias in the portfolio choices of investors, including barriers to international diversification (Errunzaand Losq (2012)), the departure from purchasing power parity (Cooper and Kaplanis(1994)) and the hedging of human capital and other non-tradable assets (Stockman and Dellas (1989), Baxter and Jermann (1995), Wheatley (2001)). Information asymmetry, the lack of financial market integration, transaction costs, inflation hedging and regulatory restrictions (such as contingency rules for insurance companies) are other possible explanations for the home bias. Finally, if hedging currency risk is expensive, then the currency denomination of the liabilities becomes important. All else equal, having large domestic currency liabilities (as the PFs do) would argue for positive home bias. Furthermore, if in the presence of market frictions the social return of domestic investments is higher than the private returns of PFs, the state would aim to target higher levels of home bias.

Several authors argue for some optimal fraction of home bias in portfolio choice among institutional investors. Such optimally diversified portfolios have been established for both US investors (Clarke and Tullis(1999), Michaud et al. (1996)) and other international investors (Lewis (1999)). The potential gains from international diversification differ across different countries, however. For instance, in a recent study by Gerke, et al. (2005), using data on indices that were calculated by Morgan Stanley Capital Investment (MSCI) from January 1980 to October 2001, the results obtained from an ex-post rolling-window analysis suggest that a home bias of 20% to 40% is a suitable domestic equity investment range for German investors.

Although the increased integration of European financial markets and the introduction of the euro as a common currency have significantly affected investors' opinions on the degree of international diversification in their portfolios, European investors' equity holdings still exhibit home bias (Meade and Mann (2002)). The issue of diversification in asset allocation for better returns becomes especially important when PFs hold significant funds. In the Netherlands, PFs hold assets worth about € 630 billion, which is 125% of the Dutch GDP (Bikker and De Dreu (2009)). International diversification has been more or less ignored by Dutch institutional investors until the mid-1990s according to Wilcox and Cavaglia (1997), witha typical Dutch institutional portfolio having a foreign exposure between 25% to 30%. Low inflation, an attractive rate of return on their portfolio holdings and the guilder as one of the world's stronger currencies in that time period seems to have persuaded Dutch institutional investors to have little need for more diversification than already achieved in their portfolios; however, the increased global integration of financial markets, the significant increase in institutional asset holdings, the introduction of a common currency provide our motivation to analyze the issue of international diversification and study the home bias in Dutch institutional investors' portfolios.

Most of the financial literature investigating home bias takes the perspective of a US investor. Research on home bias outside of US is scarce and, if available, does not explain the dynamics of home bias in mature markets. Because the gains from international diversification vary considerably across markets, there is room to study home bias in other mature markets, such as the Dutch PF industry. The availability of multi-asset data in a mature PF industry with a sufficiently long horizon provides the opportunity to study the cross-sectional variation in domestic bias in the portfolio choices of institutional investors over time and across asset classes.

We use the portfolio and balance sheet information of approximately 600 Dutch PFs over a 15-year period (1992-2006) to explore the asset allocation of Dutch PFs and analyze the relationship between Dutch PFs' characteristics and their asset allocation across markets. In our analysis, we first use descriptive statistics to quantify the existence and dynamics of home bias in

Dutch PFs. Then, in our regression analysis we investigate the co-variation between PF asset allocation and individual fund characteristics.

We find that Dutch PFs have reduced their domestic fraction of investments from 37% to 13% on an asset-weighted average basis. The change is much more pronounced in less-risky assets and is influenced by the specific characteristics of PFs. We observe that Dutch PFs' size effects are limited to their fixed-income, domestic-asset allocation, while PFs' experience influences their overall asset allocation. Both the introduction of the euro and the dot-com crisis have led to a significant downward shift in home bias.

This paper adds to the existing literature in several ways. First, there is only limited empirical research available that explains home bias using multi-assets data.[2] Second, our study has a broader scope in comparison with past studies by considering the individual characteristics of PFs. Finally, Dutch PFs are the dominant investors in local financial markets and are prominent investors in European financial markets. Hence, our study would also reflect the investment behavior of Dutch institutional investors as well as European institutional investors in general.

The rest of this chapter is organized as follows. Section 2 introduces the institutional settings of the Dutch pension system. Section 3 explains the data. Section 4 describes our research design and methodology. Section 5 presents the empirical results and, finally, Section 6 concludes our analysis.

2.2. The Institutional Settings of Dutch PFs

The Dutch pension system consists of three pillars, where the first pillar is a compulsory pay-as-you-go scheme that is referred to as General Old Age Pensions Act (AOW), the second consists of statutory, mostly defined benefits that are mixed with hybrid and defined contributions, and the third is fully funded (tax-supported), self-arranged by individuals, and comprises, for instance, insurance companies' policies. Dutch PFs constitute the second pillar of the Dutch pension system and can

[2]Bikker and De Dreu (2009) also investigate home bias in Dutch PFs but at the level of euro zone, where home bias is defined as percentage investments (p.17) in the EMU without segregating investments into asset classes. A related paper investigating Dutch PFs' investment strategies is De Haan and Kakes (2012). They find that funds buy past losers and sell past winners.

generally be divided into two broad classes: company-linked and industry-wide PFs. Industry-wide PFs can be found in specific business sectors, such as health care and services.

Table1 The evolution of number of PFs over time in relation to business sector and benefit scheme

	Pension Fund Type				Scheme Type			
Period	Industry	Company	Others	Total	Hybrid	DB	DC	Total
1992	72	723	14	809	17	810	77	904
1993	72	750	15	837	23	832	82	937
1994	74	769	16	859	27	844	85	956
1995	74	790	17	881	26	863	87	976
1996	75	811	17	903	27	872	90	989
1997	82	824	18	924	28	857	87	972
1998	85	854	18	957	28	842	87	957
1999	87	823	19	929	27	818	85	930
2000	91	796	19	906	25	799	83	907
2001	94	757	19	870	23	771	75	869
2002	100	693	16	809	16	722	68	806
2003	101	664	16	781	13	687	70	770
2004	104	631	19	754	12	657	65	734
2005	102	595	19	716	10	620	61	691
2006	92	527	20	639	9	558	50	617

Notes: Table 1 explains the number of PFs over time for different pension schemes and pension fund types over the years from 1992 to 2006. Source: DNB

Dutch Public Servants Pension Fund (ABP) is an example of an industry-wide pension fund. This pension fund caters to Dutch government and education sector employees. Company-linked PFs are, in contrast, company specific. Table 1 presents the compositions of Dutch PFs in terms of business sector and benefit type over the years. The domination of company-linked PFs in terms of number appears to be a pronounced feature of Dutch pension system, whereas industry-wide PFs appear to be superior in terms of the number of participants and total assets (see Table 2).

A unique characteristic of the Dutch pension system at the time of our data sample in comparison to pension systems in many other countries is that it entails all three types of benefit schemes, i.e. Defined Benefit (DB), Defined Contribution (DC), and a combination of these two, which is referred to as a hybrid scheme.

A significant number of both industry and company PFs offer DB pension schemes, wherein approximately 10% of company PFs offer DC pension schemes. The dominance of DB schemes over DC schemes throughout the observed period is obvious in terms of number, total assets and number of participants (see Table 2). In the years beyond our sample, many DB schemes have moved to DC.

Table 2 Sectors and benefit schemes in relation to the total assets and number of participants

	TotalAssets				NumberofParticipants			
Period	Company PFs	Industry PFs	DC Schemes	DB Schemes	Company PFs	Industry PFs	DC Schemes	DB Schemes
1992	152	59.7	4.24	218	0.92	3.02	0.04	3.99
1993	78.1	68.0	2.78	154	0.96	3.18	0.05	4.18
1994	70.1	78.5	3.01	156	0.97	3.35	0.05	4.39
1995	80.2	86.8	3.10	175	1.00	3.52	0.05	4.57
1996	90.6	197	3.45	297	1.12	5.20	0.05	6.37
1997	108	222	3.93	341	1.15	5.46	0.09	6.62
1998	126	264	2.29	401	1.17	5.50	0.07	6.66
1999	143	297	2.93	467	1.20	5.72	0.07	6.91
2000	146	311	3.23	478	1.22	5.66	0.07	6.86
2001	144	316	3.78	471	1.28	6.46	0.08	7.56
2002	132	318	3.88	438	1.26	6.77	0.08	7.84
2003	147	334	4.49	490	1.25	6.91	0.09	7.97
2004	164	374	5.34	546	1.27	7.24	0.21	8.16
2005	197	424	4.82	630	1.35	7.20	0.23	8.16
2006	207	523	4.63	742	1.29	7.02	0.23	8.09

Notes: Total assets are expressed in billions of euro, whereas the number of participants is expressed in millions of people.
Source: DNB

2.3. The Data

Our supervisory data set, which is enriched with second-pillar information, was obtained from the De Nederlandsche Bank (DNB), thesupervisory authority of the Netherlandsresponsible for the prudential supervision of PFs.This data set contains detailed portfolio and balance sheet information on Dutch PFs' holdings. The submission of PFs' annual portfolio holdings report to the supervisory authority is compulsory and is used to compile Dutch balance-of-payments statistics. Currently, more than 650 PFs are operating in the Netherlands, and our detailed data set consists of the actual annual PF holdings data of more than 600 Dutch PFs from 1992 to 2006, with asset-wise (equity and bonds) breakdowns as well as market-wise positions. The data set is an unbalanced panel, and non-sampled PFs are missing because of new entrance, mergers and acquisitions, and terminations over the observed period. Although we miss some PFs, the issue of survivorship bias is not significant considering that sampled PFs cover virtually over 95% of the total assets of the Dutch PFs industry throughout the observation period.

The information in our data set is available at the fund level. Each pension fund is obliged to submit an annual report of its portfolio positions no later than four months after the end of each financial year. This report contains information on positions in domestic and foreign assets and liabilities, in addition to profit and loss accounts. DNB's central database, which stores all of the information and processes this raw data into a workable form, is called DEBBI. The broad asset categories that can be found in the DEBBI database include equity, fixed income, money market papers, investment and money market funds and real estate. We focus our analysis on equities and bonds because these two asset categories hold the largest proportion of PFs' total assets and their data is organized into a workable, easily accessible form. The Dutch PFs are also obliged to submit information about other variables, on for example, mergers and acquisitions, the number of participants, types of participants, average ages of participants, the types of benefit schemes involved in a PF offering and sectors to which PFs belong. This information is a part of the supervisory database.

2.4. Research Design and Methodology

Considering the nature of our data, we use descriptive statistics to develop hypotheses and then construct regression models in order to test these hypotheses with the available data.

2.5. Hypotheses

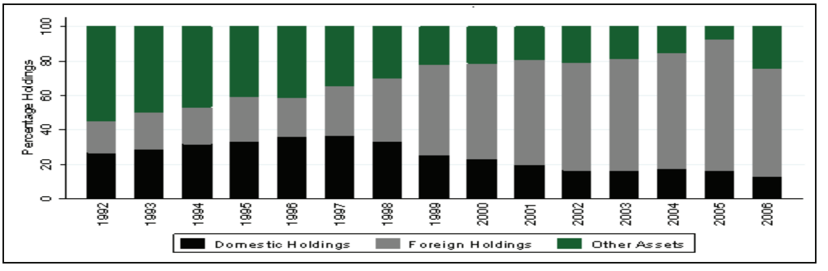
2.5.1. Home Bias Across Markets and Asset Classes

An overview of the data descriptives reveals that the fraction of domestic holdings in Dutch PFs' portfolio holdings varies between 0.01% and almost 100%. The asset-weighted, average home bias (foreign holdings) over the observed period remains at approximately 22.5% (53.8%).[3]A graphical presentation of the average domestic vis-à-vis foreign share of investments as a percentage of total Dutch PFs' holdings over time is sketched in Figure 1. This figure clarifies two important aspects: first, on average, home bias in Dutch PFs' portfolio choices is decreasing over time, i.e., it decreased, on average, from 37% in 1997 to 13.2% in 2006. We attribute the decreasing home bias to be driven by the growing integration of financial markets, increased financial knowledge and more risk awareness over time, all of which foster international diversification. Even if we take the findings of Wilcox and Cavaglia (1997) as a benchmark, we observe a significant reduction in average home bias in the portfolio choices of Dutch institutional investors over

[3] Weighted averages have been calculated by taking 'total assets' and 'number of participants' as weights but the later seems less useful so we focus only on the 'total assets' average.

time.[4]Our data seem to contradict the internationally recognized home bias puzzle because of an obviously declining trend in domestic exposures shown by our data.

Figure 1 The evolution of domestic and foreign yearly average percentage holdings of all asset classes



Notes: Figure 1 exhibits the yearly asset-weighted average domestic and foreign asset allocations of Dutch PFs as a percentage of total holdings. Here, domestic holdings = domestic equities + domestic bonds, foreign holdings = foreign equities + foreign bonds and other assets are the assets that comprise all of the asset categories other than equities and bonds, and their market of allocation is are also not reported in these reports.. The other assets comprise of money market papers, investment and money market funds, real estates and alternative investments..Source: DNB.

Second, the average home bias development during our observation period discerns two sub-periods: an era of higher and increasing average domestic bias (before and including 1997) and a period of lower and decreasing average domestic bias (after 1997) in comparison to international portfolio holdings. The steady increase in domestic bias in the era before 1997 likely resulted from appreciation of the guilder against other currencies and high fluctuations in foreign exchange and interest rates.[5] Furthermore, before 1997, Dutch foreign investment policy has been strict. In 1996, ABP, which is the largest Dutch PF, implemented the new foreign investment policy[6] that was developed by the Dutch prudential supervisor, and this implementation has been imitated by many other Dutch PFs. This activity has been accompanied by a discouraging effect on the domestic bias in Dutch PFs' asset allocations over the years following that era. Another factor that has been observed to influence home bias in the later period worth studying is the introduction of the euro as a common currency. A common notion in finance is that exchange-rate stability increases international trade. The introduction of a common currency significantly reduces exchange-rate risk, which spurs

[4]Dutch institutional investors hold about 25% to 30% of foreign exposure in their portfolio mix (Wilcox and Cavaglia(1997)).

[5]DNB annual reports from 1992 to 1997.

[6] The foreign investment policy of Dutch PFs is regulated by DNB who applied certain restrictions on capital mobility by the PFs. These restrictions were loosened around beginning of our observation period.

international trade; therefore, our expectation of a lower domestic bias in portfolio choices among Dutch institutional investors due to the inaction of a common currency seems justified.

A common theory in the financial literature is that a financial market crisis increases market volatility and shakes the trust of the (institutional) investors even in their own investment decisions. This shaken trust leads investors to follow their peers and can persuade them to invest in the markets that are well known to them so as to avoid a loss of reputation. Because domestic markets are the most explored and known to a domestic investor, we expect a higher home bias in Dutch PFs' investment behavior during the dot-com financial turmoil.[7]

Figure 2 The evolution of the yearly average percentage holdings of equities and bonds across markets

Notes: Figure 2 depicts the yearly asset-weighted averages of equities and bonds positions of Dutch PFs portfolios as a percentage of their total portfolio holdings across domestic and foreign markets.

Source: DNB.

Our available data consists of both riskier assets, such as stocks, and less-risky assets, such as fixed incomes. One question naturally arises here: does the investment behavior of Dutch institutional investors vary across asset classes in the two markets? To answer this question, we explore home bias in Dutch PFs' investment behavior across their asset mix. The average home bias in fixed incomes and equities turns out to be approximately 19.5% and 14%, respectively, over the sample period and follows diminishing patterns in both asset classes, as can be observed in Figure 2. These observations demonstrate a higher preference for domestic bonds holdings over domestic

[7]Dutch PFs held 28.7% (41%) domestic (foreign) holdings before the dot-com crisis, which decreased to 15.8% (66.9%) after the crisis on an asset-weighted assets basis.

equities in Dutch PFs trading behavior.[8] Our descriptive results seem more or less consistent with the findings of Gerke, et al. (2005), which suggest a 20% to 40% domestic investment to be a suitable range in domestic stocks for German investors. A steep rise in foreign bonds' positions (see Figure 2) in the second era can partially be attributed to an increase in Italian and French bonds' exposures because of their attractive returns and partially to inaction of the common currency. A comparison of descriptive statistics of the portfolio mix across markets before and after the introduction of the euro reveals that, on average, Dutch PFs exhibited a 9% (21%) reduction (increase) in domestic (foreign) bias in the bonds market in comparison with a 5% (15.7%) reduction (increase) in the equity market. Therefore, we expect the introduction of the euro to negatively influence domestic bias across asset classes. Though the introduction of the euro is likely to increase the correlations between the markets in the euro zone, these correlations are likely to be low in the beginning which will not fully destroy the benefits of international diversification. Over time the diversification benefits may reduce within the euro zone due to more integration of euro financial markets.

In a similar way, the dot-com financial crisis has had a much higher impact on bond as compared with equities percentage holdings across the markets, i.e., foreign fixed-incomes exposures have increased by 18%, whereas equity holdings have increased by 8% after the dot-com financial crisis. We expect the dot-com financial crisis to have an adverse impact on the domestic asset allocation decisions of Dutch PFs across asset classes but at a different magnitude.

2.5.2. Home Bias and PFs' Characteristics

While in the above discussion we concentrated on delineating home bias and its dynamics in the context of the asset allocation behavior of Dutch PFs across financial markets as well as asset classes, we will now focus on establishing the relationship between Dutch PFs' asset allocation behavior and their individual characteristics.

Experience based knowledge built up through investment activities provides the framework for perceiving and formulating investment opportunities. It allows PF management to perceive how well an investment opportunity fits into a profitable investment strategy. International investments develop new capabilities and augment the existing capabilities of a

[8] Dutch PFs hold 13% bonds in domestic markets and 29.4% equity in foreign markets on an asset-weighted assets basis.

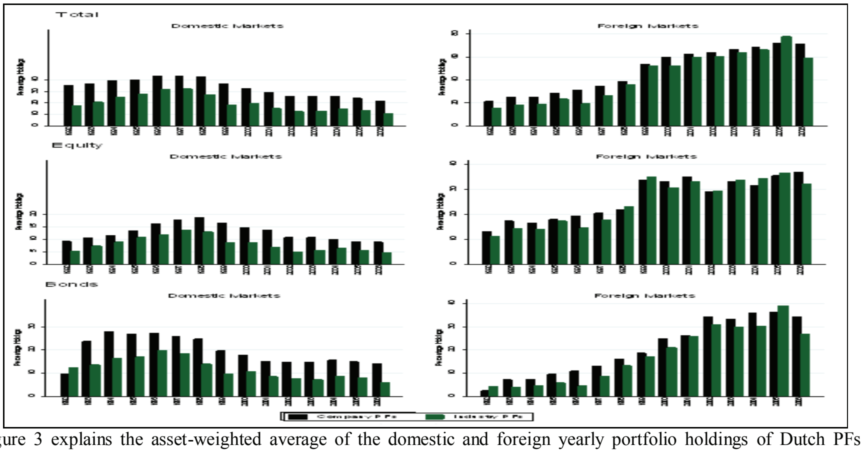
company through their operations in foreign markets (Kogut (1983)). The operational age of a PF can be seen as the accumulated investment experience, through long-term operations in international financial markets, that contributes to the general knowledge and capabilities that are required for efficient portfolio choice and portfolio risk diversification. Home bias can be viewed as a portfolio risk that precludes better returns through inefficient international portfolio diversification. We thus expect a PF's operational age to be negatively associated with home bias.

When deciding on portfolio size, an investor (PF) makes a trade-off between the increased transaction costs (decreased return) versus decreased risk due to more effective diversification by adding more securities to its portfolio (Grubel (1968)). In rational efficient markets, an investor is likely to keep adding new international securities to his portfolio so long as the marginal benefit of international diversification is greater than the marginal cost. Moreover, a common notion in finance is that trading in bulk reduces the marginal transaction costs. Now, given that scale economies allow large PFs to mitigate the effect of high transaction costs through trading in bulk, reducing portfolio risk and acquiring higher returns at this reduced level of portfolio risk, large PFsare more likely to have less home bias and better international diversification in their portfolio choice. In the Netherlands, some PFs are too big to invest in domestic markets. Their higher domestic positions would result in inefficient portfolio diversification through capturing virtually the entire domestic market, which would, thus, influence the market prices. Likewise, international diversification becomes inefficient for small PFs owing to higher trading costs. Therefore, for large institutional investors, it is inevitable to diversify their portfolio holdings internationally, whereas the converse prevails for small PFs; hence, the argument of higher trading costs in combination with scale economies could provide large PFs with more opportunities to internationally diversify their portfolio. Therefore, we ex-ante expect portfolio size to negatively influence domestic holdings.

Figure 3 compares asset allocation over time in company and industry PFs and, therein, clarifies two important points: first, on average, domestic exposures are decreasing over time for both types of PFs.

Second, on average, company PFs hold about 14% fewer domestic shares across the two markets compared to industry PFs. Appendix A demonstrates that almost half of all company PFs are small and offer DB schemes. The DB character of PFs persuades them to invest in risky assets for higher risk-adjusted expected returns because higher risk-adjusted expected returns can reduce their contributions to the pension plan.[9] Higher risk-adjusted expected returns are possible either through increasing the number of risky exposures in their portfolio choices or through increasing the international diversification of their portfolios; however, company PFs are more customized to the preferences of the employer and employees, and their services to the plan participants can be of higher quality.

Figure 3 The evolution of domestic and foreign yearly average percentage



Notes: Figure 3 explains the asset-weighted average of the domestic and foreign yearly portfolio holdings of Dutch PFs in equities, bonds and total (= equities + bonds) as a percentage of total portfolio holdings across markets as well as sectors.
Source: DNB.

This explicit choice for customization and extra service results in higher operating costs (Bikker and De Dreu (2009)). Additionally, their small size precludes them to exhibiting efficient international diversification; therefore, they may choose to increase the number of their domestic risky exposures to achieve higher risk-adjusted expected returns. On the other hand, many large industry PFs also offer DB schemes, which may tempt them to possess fewer domestic holdings or more international diversification in their portfolios to achieve higher risk-adjusted expected returns.

An important control variable that influences the asset allocations of Dutch PFs is the cover ratio.[10] The higher the cover ratio, the more assets a PF has against itsliabilities(technical provisions). A higher cover ratio also means that a PF has more buffers to cover portfolio losses.

[9] Higher returns to PFs that offer DB schemes can help to reduce sponsor contributions to the PF.

[10] It is defined as ratio of total assets to the liabilities of a PF. For every PF statutory requirement by the prudential supervisor is to maintain threshold cover ratio at 105%, and if it falls below this threshold necessary actions under the guidelines of prudent supervisor should be taken to regain the threshold within next three years.

Another important factor that may affect the portfolio choice decisions of a Dutch PF manager is the reward on higher risk-adjusted expected returns. Dutch PF managers are usually rewarded for beating a benchmark or producing superior returns. A higher cover ratio can tempt a Dutch PF manager to increase risky exposures in his portfolio holdings in pursuit of higher returns; however, by diversifying internationally he will be able to reduce his portfolio risk. Given that international diversification offers potentially higher risk-adjusted expected returns at any given level of risk and Dutch PF managers are rational, PFs with higher cover ratios are likely to exhibit more international diversification or less home bias.

2.6. The Model

Section 2.1 explained that the average percentage exposures of Dutch PFs in domestic markets significantly decreased from 37% to 13% over the observed period, and we also observe the same investment behavior across asset classes, which signifies a time effect. Section 2.2 explained some important factors, such as a PFs' size, age, pension plans, cover ratio and riskiness of the assets that may potentially influence home bias in Dutch PFs. The overall evolution of the Dutch PF industry's domestic exposures is the integrated effect of all of these factors and time. Our goal in this section is to establish a unified model that best explains our hypotheses by fitting a relationship between PFs' asset allocation behavior and their characteristics. We propose a linear panel data model to statistically test our proposed theories using standard assumptions for a linear panel data model that could encompass all of the required variables (see Appendix A for a correlation matrix between all of the potential factors in the model). We find a low correlation between PF size and operational age, which reveals that mature (a high operational age) PFs are not necessarily large and that both candidates can be model constituents, i.e., PF size could be used to test the scale economy effect, whereas PF age could be used to test the experience curve effect. A choice between domestic riskier and less-risky assets by Dutch PFs may be affected by their degree of risk averseness. Appendix A also allows us to detail the cover ratio as a control variable in our model.The correlation matrices shown in Appendix A provide us with sufficient comfort that we can include the different factors in our proposed linear panel data regression model.

We run different regression analyses of the overall ratio of domestic assets to foreign exposures that are held by each PF verses PF characteristics and fixed time effects. These regressions are also separately performed for equities and fixed incomes and are modeled as:

$$DH_{it} = \alpha_0 + \beta_0 X_t + \gamma_0 D + \varepsilon_{i,t} \quad (1)$$

$$EDH_{it} = \alpha_1 + \beta_1 X_t + \gamma_1 D + \varepsilon_{i,t} \quad (2)$$

$$BDH_{it} = \alpha_2 + \beta_2 X_t + \gamma_2 D + \varepsilon_{i,t} \quad (3)$$

Here DH_{it}, EDH_{it} and BDH_{it} stand for the ratio of domestic to foreign exposures at overall, equities and fixed income levels that are held by the i^{th} PF at time t. The variable α represents PFs' specific effects, which do not vary over time but vary across PFs. The variable β indicates the effects of each PF's specific characteristics in matrix X on ratio of domestic to foreign exposures to overall and asset class levels. The matrix X contains the logarithm of the total assets (size), operational age (age) and cover ratio. D presents a matrix of dummy variables and consists of industry, benefit, euro and dot-com dummies. The industry dummy is one if the PF is an industry PF, the benefit dummy is one if the PF is a DB-fund, the euro dummy is one after the introduction of the euro and, finally, the crisis dummy is one during the dot-com crisis. All dummies are zero otherwise. The Hausman's test leads us to apply fixed-effects regressions. In applying fixed effects, variables that do not change over time (for example, the pension plan dummy and the benefit schemes dummy) cannot be included. As these variables may provide some important insights, we also run random-effects regressions.

2.6. Empirical Results

Tables 3 to 5 present the results of the fixed- and the random-effects panel regressions defined in Equations 1-3. The second column of each table presents the regression results using fixed-effects regressions, whereas the third column shows the estimates of the same regressions using a random-effects model. In Table 3, we present the results of the Equation 1 regression explained above. Time has a significant negative impact on home bias in Dutch PFs across markets in addition to asset classes, as also evident from Figure 2. The flexible Dutch foreign investment policy, the increasing integration of financial markets, the quicker and more reliable information gathering through IT systems are potential reasons why time influences home bias.

Table 3 does not support our prior statement that scale economies, in general, provide institutional investors with more opportunity to diversify their assets across markets and, thereby, reduce their domestic bias. Similarly, according to the results depicted in Table 4, the same can be said for equities when we analyze home bias across asset classes; however, according to Table 5,PF size, adversely influences Dutch PF domestic bond exposures, suggesting that large PFs trade off more of their domestic bonds so as to increase their holdings of foreign bonds. Declining domestic exposures and growing foreign positions would also mean an overall better international portfolio diversification; hence, although scale economies offer efficient international diversification through the scaling down of domestic exposures, large PFs are conservative enough to exploit this opportunity only for fixed-income securities.

Table 3 Home bias in Dutch PFs' asset allocation behaviors

Variables	Fixed effects	Random effects
Size	0.05	-0.13*
	(0.08)	(0.65)
Age	-2.42***	-0.04
	(0.16)	(0.02)
Cover Ratio	-0.74	0.00
	(0.47)	(0.02)
Industry	-	-6.96**
	-	(2.56)
Defined benefit	-	-6.63
	-	(4.54)
Euro	-14.30***	-25.09***
	(1.04)	(0.72)
Dot-com crisis	-5.14***	-13.18***
	(0.91)	(0.70)
R^2	0.60	0.56

Notes: The dependent variable is the ratio of domestic to foreign assets. The PF size is the logarithm of the total assets held by a PF in a particular year. The cover ratio is the ratio between a PF's assets and its technical provisions. The age is the number of years that a PF has been in operation. The dot-com crisis dummy takes value 1 if period is after 2001 and Euro dummy is equal to 1 if period is after 1999. Industry dummy variable takes a value of one if the PF is an industry PF, whereas the benefit dummy variable is equal to one if the PF offers a DB scheme. Standard errors are in parenthesis. One asterisk indicates statistical significance at a 10% level, two asterisks indicate statistical significance at a 5% level and three asterisks indicate statistical significance at a 1% level. R^2 has been presented for within group and between group. For within group R^2 shows the explanatory power due to the explanatory (right hand side) variables explaining changes home bias for individual PFs.
Source: DNB

Our fixed-effects regression results indicate that experience does matter in the international portfolio diversification of Dutch PFs. Overall, we observe that experience reduces domestic bias (see Table 3) and international portfolio diversification increases as a function of the operational age of Dutch PFs. The results are not only highly statistically significant but also economically important. For instance, on average, one additional year of experience reduces home bias by 1.23% in a typical Dutch PF. The results affirm our initial expectation that more mature PFs should have a greater understanding of portfolio diversification and more portfolio risk awareness; hence, they possess a reduced home bias in their strategic asset allocations. If we use PF age as a proxy for PF maturity, our results become consistent with the findings of Alestalo and Puttonen(2006). Experienced PFs may have more portfolio diversification knowledge; however, at the same time, they become more risk-averse because they are close to their payout phase. Their deeper knowledge may help them to efficiently internationally diversify their portfolios, but their increased risk aversion due to maturity might entice them to increase the number of less-risky exposures in their portfolio holdings. Our results indicate that more experienced funds establish higher portfolio diversifications across both markets and asset classes, but these diversifications are more pronounced in fixed-income securities.

We do not find any results that explain the relationship between industry dummy variables and PFs' asset allocations using fixed-effects regressions; however, a belief in the existence of a relationship between the two persuades us to perform random-effects regressions for the same data set. At an overall sample level, our random-effects regressions indicate that industry PFs better diversify their portfolios across markets and possess a significantly lower home bias in their asset allocations in comparison to company PFs; however, at the asset class level, we observe that the entire contribution to reducing the overall home bias in industry PFs can be exclusively attributed to the fixed-income exposures of industry PFs (see Table 5). In general, industry PFs are fewer in number but many are large (see Appendix A) and probably mature at the same time. On the one hand, their large size, greater experience and conservative attitude toward asset management allow them to reduce home bias through experience-based superior portfolio diversification in fixed income assets in comparison to company PFs. On the other hand, company PFs are smaller in size but more numerous in number, and most of them are not appreciably mature. These factors may direct company PFs to curb their international portfolio diversification abilities and, thus, indicate a reason as to why they exhibit a larger home bias in comparison to industry PFs.

Table 3 indicates that the cover ratio does not influence the overall asset allocations of Dutch PFs across markets; however, it does affect the asset allocations of Dutch PFs across asset classes in the two markets. Table 4 illustrates that a higher cover ratio increases the number of domestic equity exposures in Dutch PFs' asset allocations, which contradicts our initial expectations. A higher cover ratio means more available assets to cover liabilities, and these more available assets increase the ability of a PF to endure more risks by providing a buffer against those risks. We find a very small negative economically insignificant but statistically significant correlation[11] between PF size and its cover ratio (see Appendix A), suggesting that many small PFs have high cover ratios. Given that most small PFs are company PFs that offer DB schemes,[12] a high cover ratio tempts the managers of these PFs to hold riskier exposures in their portfolio in pursuit of better returns; however, at the same time, their small size allows them to make a trade-off between foreign – costly but diversified markets – and domestic – cheap but well-known markets.

Table 4 Home bias in Dutch PFs' equity holdings

Variables	Fixed effects	Random effects
Size	0.06	-0.11
	(0.12)	(0.09)
Age	-1.23***	-0.03
	(0.22)	(0.02)
Cover Ratio	0.19**	0.06**
	(0.08)	(0.02)
Industry	-	-1.30
	-	(2.89)
Defined benefit	-	-3.68
	-	(4.98)
Euro	-12.91***	-18.30***
	(1.33)	(0.87)
Dot-com crisis	-6.99***	-10.81***
	(1.20)	(0.90)
R^2	0.28	0.27

Notes: The dependent variable is the ratio of domestic to the foreign assets. The PF size is the logarithm of the total assets held by a PF in a particular year. The cover ratio is the ratio between a PF's assets and its technical provisions. The age is the number of years that a PF has been in operation. The dot-com crisis dummy takes a value of one if the time period is after 2001, whereas the euro dummy is equal to one if period is after 1999. The industry dummy takes a value of one if the PF is an industry PF, whereas the benefit dummy is equal to one if the PF offers a DB scheme. Standard errors are in parenthesis. Two asterisks indicate statistical significance at a 5% level, and three asterisks indicate statistical significance at a 1% level. R^2 has been presented for within group and between group. For within group R^2 shows the explanatory power due to the explanatory (right hand side) variables explaining changes home bias for individual PFs. Source: DNB.

Our results indicate that they avoid risky foreign holdings (for instance foreign stocks)[13] that could be costly for them because of high transaction costs and, instead, prefer domestic risky holdings because of lower transaction costs and their familiarity with well-known markets; thus, these data explain the high fraction of riskier domestic exposures in their asset allocation. In other

[11] A very small economically significant correlation does not affect the results in our regression models; nevertheless, its statistical significance explains us the direction of co-movement of size and cover ratio.

[12] For a DB scheme, benefits are defined and higher returns actually reduce the matching contribution of the sponsor, the employer, to the PF. Bikker and De Dreu (2009) document that small PFs have a high tendency to hold domestic assets.

[13] Though international diversification reduces risk, PFs seem to prefer to diversify their international portfolio using less risky securities, for instance bonds, while domestically focusing more risky securities, for instance stocks, to avoid cost issues. Another reason to focus on bonds for their international portfolio diversification is mismatch risk (Bikker and De Dreu (2009)).

words, the liability structure in smaller Dutch PFs drives the pursuit of risky exposures in their portfolio choices across markets.

We also explore the effect of the euro as a common currency on the asset allocations of Dutch PFs. We find that the introduction of the euro has a significant negative effect on the domestic exposures of PFs' portfolio holdings overall as well as on an asset class level. Overall, we observe an approximately 14% lower home bias that is significant at a 1% level following the introduction of the euro. The reduced exchange-rate risk environment seemed to have persuaded PFs to increase their international holdings in their portfolio choices. At an asset class level, the effect of a common currency is stronger on equities than fixed-income instruments. Black and Litterman (1992) have examined the relative performances of equities and bonds using a combination of mean-variance optimization and capital asset pricing models. They find that bond portfolios are more beneficial in comparison to equity portfolios when currency hedging considered. Our results seem to be inconsistent with their study; moreover, these results seem to be consistent with the theories that exchange-rate stability positively affects international trade under the assumption that investors are risk-averse

Our regression models also capture the effect of the dot-com crisis on the trading behavior of Dutch PFs. Tables 3 to 5 present the results of the dot-com effects on the asset allocation decisions of Dutch PFs at an aggregate level and across asset classes. The effect appears to adversely affect the number of PF domestic exposures significantly, suggesting that distress in financial markets reduces the number of domestic holdings in the portfolio choices of Dutch institutional investors. This result contradicts our prior results, which indicates that the dot-com crisis increases the number of domestic exposures in the portfolio choices of investors. We offer the following reason to explain this unexpected discrepancy. Loosened restrictions14 on capital mobility have allowed Dutch PFs to invest internationally and with the introduction of the euro their domestic investment horizon has expanded to the euro zone as the associated exchange-rate risk disappeared. Now, technically, the euro zone could be considered their domestic investment region. Restrictions on capital mobility were reduced significantly at the peak of the dot-com crisis.

[14] These regulations were changed significantly at the beginning or our period and then remained unchanged, especially with regard to the cover ratio.

These restrictions then led Dutch PFs to reduce their investments in their home region when the dot-com bubble burst .Note that the effect of the dot.com crisis is larger for fixed income compared to equities. As a result, PFs curtailed their overall domestic positions (Dutch exposures) and strengthened their fixed-income positions, especially in foreign markets (euro zone) in the following years. Finally, the results from both of our fixed- and random-effects regressions demonstrate that the type of benefit scheme does not have a role in the explanation of home bias in Dutch PFs.

Table 5 Home bias in Dutch PFs' bonds holdings

Variables	Fixed effects	Random effects
Size	-0.19**	-0.27**
	(0.09)	(0.07)
Age	-2.41***	0.02
	(0.17)	(0.02)
Cover Ratio	0.01	0.01
	(0.01)	(0.01)
Industry	-	-6.21***
	-	(2.29)
Defined benefit	-	-5.01
	-	(3.61)
Euro	-11.50***	-22.87***
	(1.07)	(0.72)
Dot-com crisis	-10.09***	-18.30***
	(0.91)	(0.69)
R^2	0.50	0.47

Notes: The dependent variable is the ratio of domestic exposures to foreign holdings. The PF size is the logarithm of the total assets held by a PF in a particular year. The cover ratio is the ratio between a PF's assets and its technical provisions. The age is the number of years that a PF has been in operation. The dot-com crisis dummy variable takes a value of one if the period is after 2001, whereas the euro dummy variable is equal to one if the period is after 1999. The industry dummy variable takes a value of 1 if the PF is an industry PF, whereas the benefit dummy is equal to one if the PF offers a DB scheme. Standard errors are in parenthesis. Two asterisks indicate statistical significance at a 5% level, and three asterisks indicate statistical significance at a 1% level.R^2 has been presented for within group and between group. For within group R^2 shows the explanatory power due to the explanatory (right hand side) variables explaining changes home bias for individual PFs. Source: DNB.

2.7. Conclusions

This study provides an empirical analysis of the asset allocation behavior of Dutch PFs across multiple asset classes. We also analyze how individual PF's characteristics – such as size, age and cover ratio – drive their long-term asset allocation decisions. We find that Dutch PFs' domestic share in portfolio allocation ('home bias') diminishes over time, and that fund characteristics, such as economies of scale, experience, funding status and pension plan (DB or DC),significantly affect their asset allocation, as discussed in more detail below.

Overall, the size of a PF does not influence its asset allocation decisions across markets; however, it is relevant for the asset allocation of different asset categories across the markets. Economies of scale seem to provide large PFs with the opportunity to increase their international holdings by reducing their domestic bias but only in fixed income. Experience is found to be important in international portfolio diversification, as we observe a significantly increasing international portfolio diversification for experienced Dutch PFs across all asset classes; this decrease in domestic assets allocation is more pronounced in fixed-income financial instruments. We attribute the activity of experienced PFs to result from experience-related effects and an increasing risk-averseness for older PFs. Our results are consistent with for instance those of Alestalo and Puttonen (2006) in the sense that the PF age affects asset allocation decisions.

In contrast to industry PFs, companies PFs allocate a larger proportion of their portfolio at home. We offer the explanation that economies of scale allow industry PFs to reduce home bias through experience-based portfolio diversification but only in fixed-income assets because their greater experience might be accompanied by increased risk aversion. The introduction of the euro as a common currency (1999) significantly reduces domestic bias. Our results are consistent with the theory that exchange-rate stability positively affects international portfolio holdings assuming investors are risk-averse. We find that the dot-com financial crisis has significantly and negatively influenced the trading behavior of Dutch PFs. This effect is negative and weaker for domestic equities while positive and more robust on foreign fixed-income securities. The cover ratio is found to be a driving force in the asset allocation decisions of Dutch PFs across markets, but only in the riskier assets of lower-sized funds.

Chapter 3: Herding and Trading Among Dutch PFs

This paper provides evidence to repudiate the popular belief that Dutch PFs are long-term passive institutional traders; rather, like active traders, they trade about eight and a half percent of their portfolios on a monthly basis. Drawn from a unique data sample, our results affirm significant feedback trading strategies, both momentum and contrarian, and robust herding behavior in the investments of Dutch PFs. Our findings contradict previous evidence and suggest that both the institutional lagged performance and demand for a stock trigger contrarian investments in Dutch PFs. Trading behavior also varies substantially across asset classes. Furthermore, recent financial turmoil has had a positive impact on both turnover and herding, whereas it has negatively affected feedback trading.

3.1. Introduction

Institutional investors, such as mutual funds and PFs, are prominent in the financial markets. In particular, PFs have emerged as key traders in terms of asset holdings through their accumulations of large private savings, especially in domestic markets. The assets managed by PFs have grown rapidly since the last decade of 20th century and have reached an impressive 9.72 trillion US dollars outstanding in US, 1.83 trillion in the UK, 1.02 trillion in Japan, 861 billion in the Netherlands and 981 billion for the remaining OECD countries.[15]

This growing market capitalization by institutional investors has encouraged a heated debate among academics and professionals about the relationship between institutional trading and security prices, as discussed in Lakonishok et al. (1992), Chan et al. (1993, 2012a, 2012b), Keim et al. (1997), Jones et al. (1999), Sias et al. (1999) and Wermers (2002). Academics and professionals have suggested several theories to explain the impact of institutional trading on security prices. The empirical results of these studies are greatly divergent and inconclusive: some studies (Lakonishok et al., 1992) document no connection between institutional trade and security prices, whereas others indicate that institutional trade affects security prices. The effect of institutional trade on security prices can be stabilizing (Wermers, 2002; Sias, 2004) or destabilizing (Gabaix et al., 2006).

Proponents of institutional trade's destabilizing impact on security prices link the price pressure hypothesis to economies of scale, which emphasize that institutional holdings are much larger than individual investors' assets. Therefore, they trade heavily and in large volumes as well as shift stock prices away from their intrinsic values by creating demand pressure for particular securities (liquidity hypothesis). This drift in security prices must be transitory in case the effect is destabilizing. However, if the institutional trading is truly information based or feedback trading, then the price change will be permanent and will not necessarily destabilize security prices. Opponents of this destabilizing impact on security prices link the informed trading hypothesis to the institutional demand for securities and explain that institutional traders have much better market and security information than individual investors, which helps institutional investors buy underpriced and sell overpriced stocks. Thus, these trades contribute to the stock market efficiency by bringing the security prices back to their fundamentals through price-

[15] OECD (2006): total investments of pension funds.

adjustment process (Wermers, 2002; Sias, 2004). Studies by Bartov et al. (2000) and Szewczyk et al. (1992) also support the stabilizing effect of institutional trade on security prices. However, if institutional trading is not truly information based rather than driven by simple trading rule (i.e., buy past winners and sell past losers), it destabilizes security prices and moves those prices away from their fundamentals if others jump on the bandwagon to buy overpriced stocks and sell underpriced stocks (Lakonishok et al., 1992). Most of these studies focus on feedback trading and herding in institutional trading as the main strategies for examining the relationship between institutional trade and security prices, and yet the results are largely divergent and inconclusive (Sias, 2004; Tao Shu, 2009). The focus of this chapter is limited to the investigation of the trading activity, feedback trading and herding behavior in the trading behavior of the institutional investors, while the relation between institutional trade and security prices is beyond the scope of this chapter.

Lakonishok et al. (1992) investigate the equity holdings of more than 700 US PFs and find modest indicators of positive feedback (momentum) trading and little evidence of herding in their trading. In contrast, investigating the 'Latin American' type of PFs from the emerging markets, Voronkova et al. (2005) document a robust presence of feedback trading and herding in trading behavior of Polish PFs but do not find that trading by PFs has any significant effect on security prices. Investigating the stock holdings of 274 US mutual funds, Grinblatt et al., (1995) report a strong positive feedback trading in institutional investors (i.e., they tend to buy past winners and sell past losers). They do not observe strong herding in mutual funds. However, Wermers (2002) observes relatively higher herding and feedback trading in growth oriented US mutual funds, which is consistent with the findings of Wylie's (2005) study of UK mutual funds.

Although literature on institutional trading is abundant, the majority is constrained by quarterly or longer horizon data on mutual funds' equity portfolios or for US markets. Studies on PFs' trading outside US are sparse; in particular, international studies that employ PFs' monthly data on more than one asset class are scarce. Furthermore, views on the presence of feedback trading and herding behavior among institutional investors are mixed. Thus, this disparity suggests the need to extend the study horizon to other mature, experienced markets (e.g., Dutch PFs) to acquire more evidence to strengthen and endorse one of the premises stated above.

In this paper, we explore the Dutch PF industry to investigate feedback trading and herding in the investment behavior of mature institutional investors outside US. Among the

European countries, the Dutch pension system, with 130% of GDP[16], is second only to the UK in terms of asset holdings. The Dutch PFs are emerging as significant international institutional investors, especially in European financial markets, because the regulatory conditions restricting foreign investments have gradually eased. Therefore, understanding the behavior of these New Giants[17] is vital to comprehending the dynamics of financial markets, not only in the Netherlands, but also in Europe and US. We add to the literature in three important ways. In comparison to many other studies, we use higher frequency (monthly) data that provide more insights than the quarterly data because the market's ability to absorb large trade imbalances engendered by institutional herds is more limited over shorter time horizons.[18] In addition, Dutch PFs are important in the international financial markets due to their high volume of assets; therefore, analysis of their investment behavior may help us understand the dynamics of the financial markets in which they operate. Finally, we investigate institutional investment behavior over several asset classes, whereas distant studies are limited to equities.

Our results repudiate the theory that PFs are long-term investors; they are active traders with an average monthly turnover of approximately 8.5%. A typical PF's turnover is significantly and positively affected by its portfolio size. We find statistically significant negative feedback strategies in Dutch PFs' investment behavior at the overall sample level (i.e., contrarian strategies for both lagging institutional demand and returns). However, negative feedback strategies are more significant and meaningful at the performance level. We also observe asymmetry in the use of feedback strategies across asset classes: both negative and positive feedback strategies are realized. A robust herding effect is observable when the number of PFs active in a security each month, especially on the buying side, increases. During the recent financial turmoil, we observed a positive impact on turnover and herding and a negative effect on feedback trading.

The remainder of this article addresses the following: In section 2, we introduce the characteristics of the Dutch Pension System. This section is followed by an outline of the construction of the data sample and summary statistics in section 3. In section 4, we describe our research design and methodology. We present the empirical results in section 5, and section 6 contains our conclusions.

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[16] OECD (2006): total investments of pension funds.

[17] Dinner speech by Lorenzo BiniSmaghi at IMCB conference on "Dealing with New Giants" in Geneva, May 4, 2006.

[18] "Short-term institutional herding and impact on stock prices" by Puckett et al. (2009) - source: SSRN

3.2. The Dutch Pension System

In a characteristic unique to the Dutch pension system, the sponsor company of a Dutch PF must be a separate entity to minimize the sponsor's influence on the PF's trading decisions. In general, the PF's governing body, or board of trustees, includes equal representation from both the plan's participants and the sponsor's representatives. This body determines the PF's general strategic asset allocation across fixed-income and stocks. The trustees hire fund managers who must follow an established mandate for long-term asset allocation. Asset managers are usually rewarded for superior portfolio performance, i.e., beating the benchmark.

The Dutch pension system offers all three types of benefit schemes: Defined benefit (DB), Defined contribution (DC) and a combination of the two, called a hybrid scheme. However, DB schemes are dominant in terms of number, total assets and number of participants (Rubbaniy et al., 2010). The Dutch pension system consists of three pillars. The first pillar is an obligatory pay-as-you-go system called AOW. The second pillar is statutory, involving defined benefits mixed with hybrid and defined contributions, and the third is fully funded (tax supported) and self-arranged by individuals. Dutch PFs represent the second pillar of the Dutch pension system and can generally be split up into two broad classes: company linked and industry-wide PFs. Industry-wide PFs are primarily found in organizational sectors, such as health care and services. ABP, the pension fund for employees employed in the Dutch government and education sector, is one example. By contrast, company-linked PFs are company specific; Philips and Shell each have a PF for their employees.

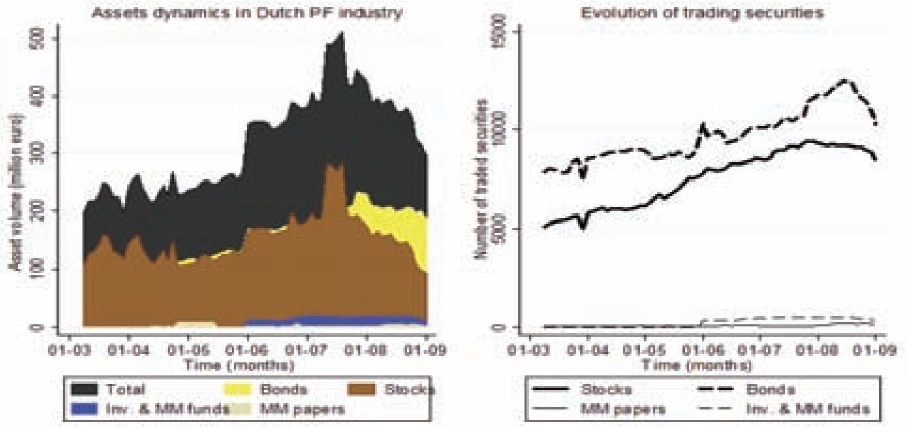
3.3. The Data Sample of Dutch PFs

In contrast to most studies, which employ only quarterly data on stocks, we use a high frequency monthly panel with multiple asset classes (stocks, bonds, money market papers and investment and money market funds). Our data set is provided by DNB[19], the prudential supervisor of Dutch PFs, and is used to compile the Dutch balance of payment statistics, Dutch holdings in international markets, the Financial Accounts and the Sector Accounts. The database includes the monthly foreign investment positions in assets and liabilities of sampled Dutch PFs,

[19] De Nederlandsche Bank (Dutch Central Bank).

insurance companies and investment institutions. However, we limit ourselves to data on PFs to study the trading behavior of the New Giants. This limitation leaves us with a monthly (unbalanced) panel of 81 Dutch PFs with information spanning from April 2003 to January 2009 and a breakdown across assets and markets.

Figure 4Assets and securities dynamics in Dutch PF industry



Notes: Figure 4 presents the over time evolution of assets and number of securities traded by Dutch pension funds. A large drop in the trend during December 2003 is due to an unfortunate data storage failure affecting more than half of the sampled PFs.

Source: DNB

The data consist of the euro value of beginning and end of month investment positions, buying and selling, price mutations, profits and losses, dividends paid and exchange-rate differences of all the assets traded by sampled PFs on a monthly basis. After omitting duplicate information, excluding inconsistent observations and eliminating observations with clear reporting errors in the data, we had 3,847,280 observations for 50,897 securities from 122 countries. Specifically, these securities consisted of 16,039 individual stocks, 32,396 fixed income financial instruments like bonds, 1,618 money market papers and 844 investment and money market funds that were traded by Dutch PFs during the observatory period. Each reported security was identified by a unique ISIN code, and we used information about all these securities in our analysis.

Figure 4 provides descriptive statistics on the final data set and shows the market value of total assets, stocks, bonds, money market papers and investment and money market funds (left panel) as well as the number of securities traded in each asset class (right panel) over time. A high volume of stocks was traded, and trading in fixed income securities showed consistent increases. Our unreported descriptive statistics reveal that a typical Dutch PF holds approximately 41% of its monthly foreign portfolio holdings in stocks, 47% in fixed income instruments and 12% in other financial instruments. The right panel of Figure 4 shows a drop in the reported securities in December 2003, which reflects a data storage failure at DNB.

Other characteristics of Dutch PFs, such as total capital invested by each PF, fund type[20] and benefit scheme offered by each PF, are reported annually, and we use data through January 2009. Our data enable us to estimate the monthly returns earned by each sampled PF on each security after adjusting for the capital gains, dividends and exchange-rates.

3.4. Research design and methodology

3.4.1. Turnover

In this section, our focus on portfolio turnover is motivated by two factors. First, portfolio turnover is one of the drivers of feedback trading and herding. Other than the individual characteristics of stocks, high past trading volume may attract investments by institutional investors that may, in turn, increase portfolio turnover and could increase the likelihood of herd in those stocks.[21] For example, stocks experiencing high turnover can become glamour stocks whose returns Granger-cause institutional trading, especially on the purchasing side (Cai et al., 2004). Second, we seek to establish whether these long-term investors trade passively. The perceived view is that, as long-term institutional investors, PFs follow a strategic asset allocation strategy of "buying and holding" assets without[22] trading them actively [Raddatz et al., (2008)] and thus rebalance their portfolios infrequently. However, this belief does not hold in the case of Dutch PFs.[23]Rubbaniy et al. (2010) show that Dutch PFs increased their foreign exposures from 18% to 76% over the period 1996-2005. In their investigation of the investment performance of Dutch PFs' equity portfolios using a micro data, Yu et al. (2009) suggest that Dutch PFs act

[20]Such as industry and company.
[21]Vivek Sharma PhD thesis, 2006 (p-34).
[22]Pension funds as passive investors, see for instance Prowse, S.D (1990) [pg/ 50] and Goergen et al. (1998) [pg. 5]

[23] The Dutch newspaper 'Volkskrant' reported that Dutch PFs have increased the rate of circulation of their foreign equity portfolio in the last few years (Volkskrant, July 14th, 2006).

passively in their investments behavior to pursue better returns. Although this evidence implicitly refers to Dutch PFs' increased trading volume or turnover rate in foreign equity holdings and suggests the need to investigate the trading activity of these institutional investors, we are not aware of studies of PFs' turnover rates or analyses of recent increases in trading activity. Because holding large deposits of assets and active trading can exacerbate stock market fluctuations (Gabaix et al., 2006) and can influence stock prices [Tao Shu (2009)], understanding the recent growth in trading activity of Dutch PFs is important. We probe Dutch PFs' trading activity using two types of turnover measures suitable to our data, both taken from the literature [i.e., Grinblatt et al. (1995) and Ferson et al. (2002)]. Both turnover measures consider the long-term weights and dynamics of securities in a PF's overall portfolio of a PF in comparison to passive benchmark weights for those securities. The difference between the two measures lies in the determination of passive benchmark weights. Grinblatt et al. (1995) propose[24]a constant weight for a particular security as the passive benchmark, whereas Ferson et al. (2002) concentrate on a changing weight as the passive benchmark. The turnover measure developed by Grinblatt et al. (1995) defines the turnover rate for PF l at time t as:

$$GT_{l,t} = \frac{1}{2}\sum_{i=1}^{M_t}\left|w_{l,i,t} - \overline{w}_{l,i,t}\right| \quad (1)$$

where $W_{l,i,t}$ is the weight of the ith security in the portfolio ofa PF l at time t, $\overline{w}_{l,i,t}$ is the benchmark weight of some passive strategy and M_t is the total number of securities in the portfolio of PF l at time t. Grinblatt et al. (1995) assume a constant weight strategy for the passive benchmark and therefore:

$$\overline{w}_{l,i,t} = w_{l,i,t-1} \quad (2)$$

[24]Grinblatt et al. (1995) - pg. 1090, develop a momentum measure to quantify the average changes in the weights of the stocks in the fund's portfolio that experienced high (low) returns in some historical bench mark period. This concept has been used by Raddatz et al. (2008) to develop a turnover measure and attribute this measure to Grinblatt et al. (1995).

The constant weight strategy explains the GT measure as a measure that computes the changes in the weights of stocks in the portfolio of a PF *l* at time *t* compared to (the passive strategic/passive bench mark) the portfolio where no portfolio revision been made. The average of this turnover measure over time shows the standard turnover statistic for fund *l*.

Ferson et al. (2002) the same measure as Grinblatt et al. (1995), denoted as $FKT_{l,t}$, but assume a changing weight strategy for the passive benchmark. Thus, their passive benchmark weight for *ith* security at time *t* held by PF *l* is defined as:

$$\bar{w}_{l,i,t} = w_{l,i,t-1}\left[\frac{1+r_{l,i,t}}{1+r_{l,p,t}}\right] (3)$$

$$\text{and } r_{l,p,t} = \sum_{i=1}^{M_{t-1}} w_{i,t-1}\, r_{l,i,t} (4)$$

where $r_{l,i,t}$ is the holding period rate of return of PF *l* for ith stock over period *t-1* to *t* and $r_{l,p,t}$ is the overall portfolio return of PF *l* at time *t*. Taking the averages of $GT_{l,t}$ and $FKT_{l,t}$ across time result the standard turnover statistics for PF *l* and averaging both measures over PFs gives overall turnover measure (GT and FKT). Testing H_0: $GT = 0$ or H_0:$FKT = 0$ is akin to saying that Dutch PFs follow a passive trading strategy.

We further extend our analysis by performing statistical inference, using fixed effect regressions, for turnover across PFs to explore the role of pension fund size and the 2007 global crisis in explaining the variation in turnover. We measure size as the logarithm of the pooled assets that a PF holds at the beginning of the month and run a regression analysis, controlling for time and total portfolio returns of a PF, as in:

$$T_{lt} = \alpha_l + \beta_s size_{lt} + \beta_c crisis + \beta_r returns_{lt} + Time + \varepsilon_{l,t} (5)$$

Here, T_{lt} is the percentage turnover of PF *l* in time t; β_s, β_c, and β_r are the parameters capturing PF's size, crisis and portfolio returns' effects, respectively. α_l is the PF fixed effects, and we incorporate the fund-time correlation in the form of error term $\varepsilon_{l,t}$. Similar regressions are also performed using lag returns and by breaking the portfolio returns into individual asset class returns of stocks, bonds, investment and money market funds and money market papers.

3.4.2. Feedback Trading Strategies

Stocks experiencing high turnover can become glamour stocks. Returns on such stocks have been shown to Granger-cause institutional trading, especially in purchasing (Cai et al., 2004). Thus, a security's history in trading activity and performance may affect the institutional demand[25] for the security, and glamorous stocks, such as ebay.com, may observe higher levels of herding than Sears.[26] Using turnover as a proxy for trading activity, we also examine whether the stocks with higher turnover attract more investors and contribute to investors' herding behavior.

In their recent investigations, Grinblatt et al. (1995), Wermers (2002) and Sias (2004) conclude that institutional investors use positive feedback investment strategies or momentum trading. A fund is called a momentum trader if it buys past winners and sells past losers, whereas the reverse is true for a contrarian investor. In the literature, several measures have been used to gauge the presence of momentum trading in institutional investors' trading behavior; however, we use the Sias (2004) momentum measure to probe whether past performance drives the institutional demand for a security and changes in portfolio allocations among the Dutch PFs. This measure is based on the idea that securities with higher past returns are more likely to be bought or sold. Following Sias (2004), we apply the following to capture the effect of k-period lag security returns on purchases in the current period:

$$P_{i,t} = \alpha + \beta_1 P_{i,t-1} + \beta_2 R_{i,t-k} + \eta_t + \varepsilon_{i,t} \quad (6)$$

$$\varepsilon_{i,t} = \nu_t + \mu_{i,t} \quad (7)$$

Here, $P_{i,t}$ expresses the current institutional demand for security and is defined as the fraction of PFs involved in purchasing the *ith* security at time *t*. $R_{i,t-k}$ is the *k* periods lag-returns

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[25] It is defined as the proportion of buyers of a security among those who are active in that security's trading.
[26] Sharma (2006).

for security i, and η_t is the time dummy The error term, $\varepsilon_{i,t}$, has a time component v_t, so that estimation of the parameters α, β_1 and β_2 cluster the errors at the time level, and the inference is equal to that obtained from the average of the period-by-period coefficients. Here, the parameter β_1 measures the sensitivity of the institutional demand for a security to its lagged demand, and $\beta_2$measures the sensitivity of the fraction of a security purchased to its k-period's lagged return.[27]

3.4.3. Herding among Investors

Herding can be understood as a special type of feedback trading. It measures the degree of correlated trading among identical or homogeneous groups of investors and shows the average tendency of traders to end up on the same side of trading for the same security at the same time. At the macro level, considering the financial market as a whole, the number of buyers for a security should be in equilibrium with the number of sellers, and therefore, herding should not be possible. However, in any subset of a financial market, such equilibrium may not be found because the number of buyers for a particular security may exceed the number of sellers, or vice versa. Thus, herding can occur in a group of similar investors rather than among random traders. This intuition leads us to investigate herding in the trading behavior of Dutch PFs as an investor group.

As in recent studies by Grinblatt et al. (1995), Wermers (2002), Lobao et al. (2002), Wylie (2005) and Voronkova et al. (2005), we use the measure from Lakonishok et al. (1992) (hence forth LSV)[28] to quantify herding among institutional investors and to compare our results with the literature. The LSV herding measure for security i at time $t$is defined as:

$$LSV_{i,t} = \left| \frac{B_{i,t}}{N_{i,t}} - P_t \right| - AF_{i,t} \qquad (8)$$

[27] For details please follow Raddatz et al. (2008) [pg. 36].

[28] It is based on the idea that if there is no herding, the probability of buying should be equal to the probability of selling among assets.

where $LSV_{i,t}$ is the herding measure for the *ith* security at time *t*. $B_{i,t}$ is the number of PFs buyers of the *ith* security at time *t* and follows a binomial distribution with probability of success P_t. P_t is the expected number of buyers at time *t*. $N_{i,t}$ is the total number of active PFs for ith security at time *t,* and $AF_{i,t}$ is the adjustment factor to allow for random variation around P_t under the null hypothesis of independent decisions by the PFs and is the expected value of $| B_{i,t}/(N_{i,t}) - P_t |$ (see Appendix A). The overall herding measure LSV is the average of $LSV_{i,t}$ over all securities and periods. A positive value of herding that differs significantly from zero will indicate a herding behavior among Dutch PFs under the assumption of normality.

A further partition of the herding measure into buy herding measure ($BLSV_{i,t}$) and sell herding measure ($SLSV_{i,t}$) allows us to investigate the strength of herding on both sides of trading. The classification of a herding measure for the ith security into one of these subgroups is based on the idea that, in a subgroup, all of the PFs trading the ith security during the time t should have a higher degree of buying or selling than what would be expected from random buying or selling. Thus, the buy and sell herding measures are distinguished based on the following criterion:

$$BLSV_{i,t} = LSV_{i,t} \text{ if } \frac{B_{i,t}}{N_{i,t}} > P_t \tag{9}$$

$$SLSV_{i,t} = LSV_{i,t} \text{ if } \frac{B_{i,t}}{N_{i,t}} < P_t \tag{10}$$

The averages of $BLSV_{i,t}$ and $SLSV_{i,t}$ over all securities and periods give us the overall buy and sell herding measures (i.e., BLSV and SLSV), and we perform their statistical inferences using the criterion described above.

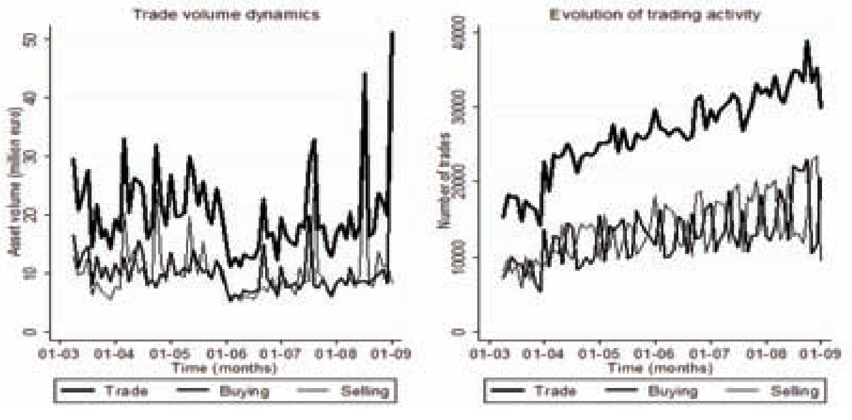
3.5. Empirical results

3.5.1. Turnover

Figure 5 displays the turnover dynamics of Dutch PFs during the analysis period. This figure shows high trading activity in the foreign portfolios of Dutch PFs from 2003 to the end of 2005 and increasing trading activity in general over the investigation period. At the beginning of

2003, the stock market rallied after two years of bad performance[29] and began showing attractive returns.

Figure 5Trade volume and trading activity dynamics in Dutch PF industry



Here, Trade = Buying + Selling. A large drop in the trading activity in December 2003 is due to a major data storage failure at DNB. Beginning on January 1st, 2006, the statistical reporting guidelines of DNB for Dutch PFs no longer required them to report all of their legal transactions. Instead, DNB required them to report their economic positions, leaving out all (reverse) repurchases, securities lending/borrowing and sell-buy-backs. Therefore, a big drop in reported transactions can be seen in January 2006. Source: DNB

The rally in stock market performance led the investment managers of Dutch PFs to change the strategic asset allocations approved by their board of trustees (Bikker at al., 2007). This change resulted in an increase in their trading activity, particularly in equities, which was primarily driven by selling their securities, as seen in Figure 2. Large swings in buying and selling toward the end of the sample period seem attribute to the global financial crisis. Highly volatile market conditions and bad returns on equities during times of crisis force risk-averse investors such as PFs to change both their strategic and actual allocations. During a crisis, such changes have been accompanied by a flight to quality.[30]

Applying a t-test to our whole sample results in significantly positive mean turnover statistics of 8.20% and 8.70%, for Grinblatt et al. (1995) and Ferson et al. (2002) turnover

[29] For instance compare to the MSCI index.

[30] Both left and right panels of Figure 1 very cleary indicate that during crisis Dutch PFs have inclined towards bonds, a comparatively safe assets; and thus mimic a financial markets phenomenon called 'flight to quality'.

measures, respectively. These results are more than double the average monthly percentage change in the assets of Chilean PFs observed by Raddatz et al. (2008) and are comparable with the quarterly turnover of 39% for Dutch PFs reported by Bikker at al. (2007). These results suggest that a typical Dutch PF trades an average of approximately eight and a half percent of its foreign portfolio in a month, disproving the theory that PFs are generally infrequent (long-term) traders. Furthermore, both measures are very similar, suggesting that relative returns[31] make no significant contribution to the changes in turnover.

Table 6 Turnover statistics across asset classes

	Turnover				
Measures	Overall	Stocks	Bonds	MM papers	Inv. & MM funds
Grinblatts et al. (1995)	8.20*** (0.46)	8.73*** (0.58	7.28*** (0.38)	31.33*** (2.92)	7.73*** (0.82)
Ferson et al. (2002)	8.70*** (0.47)	9.59*** (0.57)	7.41*** (0.38)	29.90*** (3.00)	8.07*** (0.83)

Notes: Table 6 shows the overall mean turnover vis-a-vis mean turnover across asset classes computed by the turnover measures of both Grinblatts et al. (1995) and Ferson and Khang (2002). The numbers are percentages because both the weights and returns are multiplied by 100. Standard errors are in parentheses, and T-tests are two tailed. Three asterisks indicate statistical significance at 1% level.

Source: DNB

By splitting our data into four different asset categories, we can also identify the turnover measures across individual asset classes, as shown in Table6.[32]

We observed significant variations in turnover across different asset classes, with stocks showing the highest average turnover and bonds showing the lowest average turnover; these changes are significantly different from zero at one percent level. Because riskier assets like stocks are comparatively easier to trade in financial markets to obtain the desired levels of portfolio allocations, the liquidity of these assets may explain the high turnover among stocks.

[31]Ferson and Khang's (2002) measure encompasses the weight of relative returns in the construction of passive benchmarks.

[32] From January 1st, 2006, the statistical reporting guidelines of DNB for Dutch PFs no longer obliged them to report all of their legal transactions. Instead, DNB required them to report their economic positions, leaving out all (reverse) repurchases, securities lending/borrowing and sell-buy-backs. Therefore, a large drop in reported transactions was seen in January 2006. To avoid confusion between the period before this reporting requirement change and before the crisis, we analyzed both the total sample as well as a selected sample (from January 2006 forward) but presented the results for the latter because the results do not change significantly.

To explore the significance of fund size and the recent financial turmoil in explaining variations in turnover, we ran a regression for turnover Equation 5. The fixed-effects results are reported in Table7. The first column of Table7 provides loadings of factors for Equation 5 using the measure from Grinblatts et al. (1995), whereas the second column presents effects of the measure from Ferson et al. (2002) for the same equation using lag-returns. We found that PF size had a highly significant positive effect on turnover rate for both measures. The number 4.99 in Table7 gives the economic interpretation of size's effect on turnover: a ten percent increase in the portfolio size of a typical PF increases its turnover by almost five percent. We also observed a strong positive correlation between the number of countries in which a PF invests and its turnover, suggesting that a PF that diversifies its investments into different countries also has a higher turnover rate. In aggregate, the two results suggest that scale economies allow large PFs to access and trade even in those international financial markets that small PFs cannot easily explore for new investment opportunities, possibly due to cost effects. Furthermore, by hiring a number of professionally qualified sophisticated investment managers[33] and thereby acquiring improved access to more profitable securities, larger PFs have more trading opportunities than smaller ones. To access these investment opportunities, large PFs must trade differently at different locations (i.e., selling assets at some places and buying at other places). Thus, their trading activity increases.

The turnover measures in both Grinblatts et al. (1995) and Ferson et al. (2002) show an approximately two percent higher turnover rate during the crisis; this change is significant at one percent level. One explanation for this higher turnover during a crisis is that Dutch PFs do not continuously rebalance their portfolio allocations in order to follow their required strategic asset allocations; therefore, any bad (good) stock market performance generates free float (i.e., difference between the actual and strategic portfolio allocations) in their overall portfolios. Recent financial turmoil eliminated a significant number of those risky assets in the portfolio holdings of Dutch PFs[34] that generated the aforementioned free float. Distress in the financial markets led Dutch PFs to actively rebalance those assets to align them with their long-term asset allocations and thus triggered higher turnover in trading during (after) the crisis period.

[33] For instance, ABP alone employs approximately 400 investment managers.

[34] Radio Netherlands (30/01/09) (http://www.expatica.co.uk/news/local_news/Pensions-in-the-Netherlands-hard-hit-by-crisis_49119.html)

Financial wisdom suggests that higher portfolio returns improve the funding ratio of PFs and provide PF managers with more buffers against financial risks. Because PF managers are rewarded for producing superior returns, an overall good performance raises the funding ratio and, in turn, may persuade them to trade more in pursuit of more returns.

Table 7 Turnover regressions (fixed effects) in Dutch pension funds

	Lagged returns			
Variables	Grinblatts et al.	Ferson&Khang	Grinblatts et al.	Ferson&Khang
PF Size	4..09***	4.41***	4.39***	4.99***
	(0.62)	(0.81)	(0.02)	(0.78)
Crisis	1.24*	1.65***	1.68*	2.05***
	(0.36)	(0.40)	(0.37)	(0.40)
Lagged portfolio returns	-0.02	-0.04	-	-
	(0.06)	(0.08)	-	-
Lagged stocks portfolio returns	-	-	0.02	0.05
	-	-	(0.08)	(0.11)
Lagged bonds portfolio returns	-	-	0.10	-0.36
	-	-	(0.16)	(0.29)

Notes: Table 7 reports the results of fixed effect regressions. The dependent variable is the turnover measure from Grinblatts et al. (1995) and Ferson and Khang (2002). PF size is the logarithm of total assets. The first two columns show regressions with portfolio returns, whereas the latter two columns present regression results with asset class portfolio returns (i.e., portfolio stock returns and portfolio bonds returns). Standard errors are in parentheses, and T-tests are two tailed. The numbers are percentages because both the weights and returns are multiplied by 100. Two asterisks identify statistical significance at 5% level, and three asterisks indicate statistical significance at 1% level. Crisis dummy takes value 1 if the period is after July 2007. Source: DNB

To explore whether high turnover rate is associated with lag-portfolio performance, we included lag portfolio returns in our regressions. Our argument does not find supporting evidence from the data because we found that turnover was unaffected by lag-portfolio returns. The results remain unchanged even after a further partition of lag-portfolio returns into lag individual asset class returns generated by each asset class in the portfolio. These results seem to contradict the theory of glamour securities, in which turnover corresponds to increased lag-returns.

Active trading by Dutch PFs could explain these unusual results. This active trading suggests that PF managers make investment decisions throughout the month, but aggregate reports are made at the month’s end. The intra-month affective returns generated by some securities in the portfolio during the first half of the month that could prompt turnover during the second half are reported as contemporaneous returns, and the turnover may actually be driven by these contemporaneous portfolio returns. This finding leads us to think that near past or contemporaneous returns may have a different impact on trading decisions than those in the distant past. To see changes in turnover under contemporaneous performance and to investigate this possibility, we replaced the lag portfolio returns with contemporaneous portfolio returns in our regressions. The results are reported in Table 8, but we did not observe any significant change in the results at the overall sample level.

Table 8 Turnover regressions (fixed effects) in Dutch pension funds

	Contemporaneous returns			
Variables	**Grinblatts et al.**	**Ferson&Khang**	**Grinblatts et al.**	**Ferson&Khang**
PF Size	4.42***	4.99***	3.02***	3.34***
	(0.62)	(0.78)	(0.39)	(0.50)
Crisis	1.50**	1.78***	1.53***	1.74***
	(0.36)	(0.39)	(0.37)	(0.39)
Portfolio returns	-0.10	-0.10	-	-
	(0.06)	(0.08)	-	-
Stocks portfolio returns	-	-	-0.12**	-0.17**
	-	-	(0.08)	(0.11)
Bonds portfolio returns	-	-	-0.08	0.09
	-	-	(0.16)	(0.22)

Notes: Table 8 reports the results of fixed effect regressions. The dependent variable is the turnover measure from Grinblatts et al. (1995) and Ferson and Khang (2002). PF size is the logarithm of total assets. The first two columns show regressions with portfolio returns, whereas the latter two columns present regression results with asset class portfolio returns (i.e., portfolio stock returns and portfolio bonds returns). Standard errors are in parentheses, and T-tests are two tailed. The numbers are percentages because both the weights and returns are multiplied by 100. Two asterisks indicate statistical significance at 5% level, and three asterisks indicate statistical significance at 1% level. Crisis dummy takes value 1 if the period is after July 2007. Source: DNB

However, we determined that contemporaneous portfolio stock returns significantly influence turnover significantly when contemporaneous portfolio returns are further partitioned into contemporaneous individual asset class returns generated by each asset class in the portfolio. The results are not only statically significant but also economically valuable. For example, a ten percent increase in the stock returns decreases portfolio turnover by approximately two percentage points. Higher contemporaneous returns on risky assets in the portfolios of Dutch PFs may partially explain their portfolio turnover. One could argue that good returns on stocks portfolio may encourage PF managers to invest more heavily in riskier assets, but the strategic limits for risky assets do not allow them to increase the risky portion of their portfolio. Thus, if the risky portion of the portfolio is producing good returns, the overall portfolio turnover reduces because PF managers tend to hold good performers in their portfolios for longer time periods.

3.5.2. Feedback Trading Strategies

Several authors have observed that institutional investors follow feedback trading strategies, especially momentum strategies (Grinblatts et al., 1995; Sias, 2004; Voronkova et al., 2005; Wermers, 2002; Wylie, 2005). A momentum investor buys the past winners and sells the past losers, whereas a contrarian investor does the opposite. To investigate feedback trading in Dutch PFs' investment behavior, we followed a regression model developed by Sias (2004) as explained in Equations 6 and 7. A number of regressions of fraction of buyers buying a certain security at time t on security's lag-demand, returns and lag-returns are performed on the whole, as well as at the level of each asset class, and the results are presented in Table 9. Two results are presented in Panel A of Table 9: (i) Dutch PFs are contrarian investors on the level of a security's returns vis-à-vis lag-demand for the security, and (ii) the degree to which a PF acts as a contrarian investor is more sensitive to the most recent returns than to the distant past performance of a security. We found that the effect of a security's lag institutional demand on fraction of purchase is statistically significant but not economically important. However, the results concerning the effect of a security's performance on its fraction of purchase are not only highly significant but also economically important. For example, a ten percent rise (drop) in security's current returns decreases (increases) its probability of being purchased (sold) by a typical Dutch PF by 1.69 percent. Our results seem inconsistent with earlier works that classify institutional investors as momentum traders (Grinblatts et al., 1995; Wylie, 2005; Raddatz et al., 2008; Wermers, 2002 Sias, (2004). One possible explanation for this contrarian behavior among Dutch PF managers may lie in the beliefs that certain securities have reached a point of returns reversal (i.e., past good (bad) performers will now produce bad (good) returns). Thus, active trading behavior coupled with the belief in return reversals increases (decreases) the likelihood that recent poor performers will be included (excluded) in the portfolios of Dutch PFs. We also ran the same regressions including lag-returns, higher lag-returns and institutional demand for a security. The results are highly significant and indicate that the probability that a security will be included in the portfolio of a typical PF increases gradually with a record of good performance in the distant past. This finding confirms the presence of contrarian investment behavior among Dutch PFs.

One reason for the economically insignificant effect of lag institutional demand for a security on its current fraction of purchase could be our choice to aggregate results for all asset classes, although some of the lag institutional demand for assets may have a higher significant effect than the others. Furthermore, the performance effect on a security's fraction of purchase could also vary across asset classes.

Table 9 Sias (2004) Momentum regressions (fixed effects)

	Panel A: Momentum regressions for all assets					
All assets	Overall	Before crisis	After crisis	Overall	Before crisis	After crisis
Lag-demand	-0.001 (0.002)	-0.091*** (0.003)	0.007** (0.003)	-0.001 (0.002)	-0.091*** (0.002)	0.008** (0.003)
Returns	-0.169*** (0.009)	-0.137*** (0.013)	-0.166*** (0.013)	-0.073*** (0.009)	-0.047*** (0.014)	-0.089*** (0.014)
	Momentum regressions for individual asset classes					
Stocks						
Lag-demand	0.158*** (0.004)	0.127*** (0.005)	0.077*** (0.005)	0.158*** (0.004)	0.127*** (0.005)	0.077*** (0.005)
Returns	-0.176*** (0.009)	-0.182*** (0.014)	-0.166*** (0.013)	-0.012 (0.009)	-0.006 (0.014)	-0.018 (0.014)
Bonds						
Lag-demand	-0.055*** (0.002)	-0.160*** (0.003)	-0.034*** (0.003)	-0.055*** (0.002)	-0.159*** (0.003)	-0.034*** (0.003)
Returns	-0.139*** (0.019)	0.025 (0.028)	-0.116*** (0.027)	-0.166*** (0.020)	-0.037 (0.029)	-0.174*** (0.029)
Lag-demand	-0.122*** (0.037)	-0.237*** (0.061)	-0.071 (0.046)	-0.128*** (0.036)	-0.247*** (0.061)	-0.075 (0.046)
Returns	-0.626 (0.433)	-0.425 (0.459)	-1.038 (1.066)	-0.117 (0.425)	-0.087 (0.417)	-1.542 (1.889)
Lag-demand	0.140*** (0.020)	0.081** (0.029)	0.067 (0.029)	0.142*** (0.019)	0.079** (0.029)	0.069** (0.029)
Returns	-0.191*** (0.068)	-0.137 (0.103)	-0.153 (0.097)	-0.002 (0.074)	-0.156 (0.114)	0.077 (0.105)

Notes: Table 9 presents the result of momentum regressions. The dependent variable is the fraction of buying a security. Numbers in fraction are coefficient of regression results. Standard errors are in parentheses, and T-tests are one tailed. Two asterisks indicate statistical significance at 5% level, and three asterisks identify statistical significance at 1% level. Source: DNB

To explore the explanations for these potential questions, we also ran the Sias (2004) regressions for individual asset classes; the results are presented in Panel B of Table 9. We found a significant presence of feedback trading and its obvious fluctuations across asset classes. The risk character[35] or characteristics of an asset class seem to correlate with its tendency toward momentum or contrarian investments. For example, the institutional lag-demand for a riskier asset like a stock positively influences its fraction of purchase, thereby suggesting a tendency toward momentum trading by the Dutch PFs for stocks experiencing high institutional lag-demand. However, past institutional demand for less risky assets, such as bonds, negatively affects to its current fraction of purchase, indicating that Dutch PFs tend to sell the less risky assets that have been most attractive to investors in the past. In general, as far as institutional lag-demand for assets is concerned, Dutch PFs are momentum investors for riskier assets and contrarian investors for less risky assets. Considering a security's current and past performance, Dutch PFs are contrarian investors, and this investment behavior is more pronounced in riskier assets as well as for the most recent returns. We found a serial correlation in returns that could explain the presence of contrarian trading among Dutch PFs. Thus, in contrast to earlier findings

[35] In finance literature, it is well-developed notion that stocks are riskier than bonds.

by Grinblatts et al. (1995), Wylie (2005) and Wermers (2002), the institutional lagged demand, rather than performance, drives momentum trading in risky assets such as stocks. Furthermore, both contemporaneous and lagged performance triggers contrarian investment behavior among institutional investors.

Our investigation period also spanned the recent financial turmoil (2007) and thus provided an opportunity to investigate feedback trading by Dutch PFs during this crisis. We found that the global crisis had an overall positive impact on a typical Dutch PF's probability of feedback trading based on a security's lag and contemporaneous performance of a security and a negative impact based on the institutional lag demand for that security (i.e., we found a decreasing degree of contrarian investments in lag institutional demand for security and increasing degree of contrarian behavior in a security's contemporaneous and lag performance during financial turmoil). The earlier change is attributed to all asset classes; however, later change is mainly triggered by less risky assets. Before the global crisis and during our period of observation, the funding ratio of the Dutch PF industry was well above the legal benchmark (105%). The global crisis eliminated a significant number of risky assets in Dutch PFs' portfolios, and many of them fell well below the benchmark. This decreased the portfolio weights of riskier positions and widened the gap between strategic and actual asset allocation. To balance this gap, they had to sell less risky assets, such as bonds, and buy riskier assets, such as stocks. They kept stocks that performed well during this crisis in their portfolios, and they also purchased more value stocks. This activity reduced the level of contrarian investments during the crisis time or, in other words, reduced their odds of feedback trading in risky securities. Meanwhile, acquiring strategic benchmarks required them to sell lower-risk assets like bonds, which increased selling and thus spurred contrarian investments in them.

3.5.3. Herding

Table 5 details the main findings of the LSV herding measure computed for the Dutch PFs' data. Panel A of Table 4 presents the LSV herding measure for the whole sample of Dutch PFs, averaged over the observation period and across all asset classes. This percentage is 8.14% and is significant at the 1% level. This number is not only statistically highly significant but also economically important. Economically, this number translates as follows: if 100 PFs are active in the same security in the same month, then 8.14 more PFs are trading on the same side of the market than would be expected under the null hypothesis of random selection of securities. This result is higher than Lakonishok et al.'s (1992) study of US PFs (2.7%), Grinblatts et al.'s (1995) study of US mutual funds (2.5%), Wylie's (2005) study of UK mutual funds (2.5%) and Raddatz et al.'s (2008) study of Chilean PFs (2.26%) but is less than Voronkova et al.'s (2005) study of Polish PFs (22.6%). We also observed herding asymmetry in Dutch PFs' investment behavior, indicating that herding is more common in buying than in selling securities. One reason for the rather large values of herding in trading by Dutch PFs, when compared to the values in other studies, is that Dutch PFs outsource their asset management. Many small Dutch PFs hire the same large reputed asset management firms for their portfolio management and likely have the same asset allocations in their portfolios. Even if they oversee their own portfolio management, small Dutch PFs may mimic the investment behavior of large PFs - a widespread belief about the small investors - and thus may add to the LSV herding measure. To investigate these possible factors, we divided the PFs into five different quantiles, with respect to their portfolio size or their market capitalization, and computed the LSV herding for each group. We found a higher LSV herding measure in lower quantiles, which supports our theory. Although we aggregated our herding measure across all assets and over the entire time span, we were also interested in determining of Dutch PFs herd only in specific securities and in particular periods. To address the question of whether an asset class's characteristics affect institutional herding, we divided our sample into four asset categories[36] and split the complete time span into before and after crisis episodes. The results are also reported in Panel B of Table 10. As expected, we noted an obvious variation in herding measures across different asset classes, with money market papers exhibiting the highest herding and stocks experiencing the lowest herding among Dutch PFs.

On average, we observed higher herding with less risky assets than among riskier assets. Furthermore, less risky assets contributed more to average buy herding, whereas riskier assets contributed more toward average sell herding. If we combine herding results with the turnover results from Table6, a possible explanation for low herding in riskier assets emerges: because of high trading activity associated with riskier assets, PFs adjust their positions more rapidly with riskier assets to attain their desired levels of strategic asset allocation.

[36] Stocks, bonds, money market papers and investment and mutual funds.

Table 10 Average herding measurement in Dutch PFs

Panel A: Average herding measures for all assets			
All assets	Over all	Before Crisis	After Crisis
Average Herding	8.14***	8.06***	8.22***
	(0.04)	(0.06)	(0.05)
Buy Herding	8.67***	8.77***	8.58***
	(0.05)	(0.08)	(0.07)
Sell Herding	7.58***	7.32***	7.83***
	(0.05)	(0.07)	(0.07)
Panel B: Average herding measures for individual asset classes			
Stocks			
Average Herding	4.92***	5.17***	4.68***
	(0.05)	(0.07)	(0.07)
Buy Herding	6.61***	7.18***	6.07***
	(0.07)	(0.10)	(0.10)
Sell Herding	3.41***	3.42***	3.39***
	(0.07)	(0.11)	(0.10)
Bonds			
Average Herding	5.39***	5.98***	4.94***
	(0.07)	(0.11)	(0.09)
Buy Herding	8.82***	12.50***	6.39***
	(0.10)	(0.18)	(0.12)
Sell Herding	2.01***	0.59***	3.30***
	(0.09)	(0.11)	(0.13)
MM Papers			
Average Herding	13.57***	13.21***	14.42***
	(0.80)	(0.98)	(1.33)
Buy Herding	17.34***	16.96***	18.24***
	(1.27)	(1.59)	(2.04)
Sell Herding	10.38***	9.98***	11.27***
	(0.97)	(1.18)	(1.70)
Investment & MM Funds			
Average Herding	5.24***	5.75***	4.69***
	(0.34)	(0.46)	(0.49)
Buy Herding	6.28***	6.38***	6.16***
	(0.39)	(0.54)	(0.56)
Sell Herding	4.29***	5.15***	3.37***
	(0.54)	(0.74)	(0.78)

Notes: Table 10 reports the results of herding measurements in Dutch PFs' foreign portfolios. Total, buy and sell herding measures are presented for all assets (overall), at individual asset class level, for crisis (2007) analysis. The results are percentages; standard errors are in parentheses, and T-tests are two tailed. Three asterisks indicate statistical significance at 1% level. Source: DNB

On average, we observed higher herding with less risky assets than among riskier assets. Furthermore, less risky assets contributed more to average buy herding, whereas riskier assets contributed more toward average sell herding. If we combine herding results with the turnover results from Table6, a possible explanation for low herding in riskier assets emerges: because of high trading activity associated with riskier assets, PFs adjust their positions more rapidly with riskier assets to attain their desired levels of strategic asset allocation.

Significantly higher overall herding during times of crisis is attributed primarily to the average sell herding. Less risky assets appear to be major drivers of average sell herding. We contend that stock market turbulence negatively affects the equity share in the portfolios of Dutch PFs and enlarges the gap between strategic and actual equity allocations.

Table 11 Average herding and relative activity

	Number of PFs active in a stock month					
All assets	**≥2**	**≥5**	**≥10**	**≥15**	**≥20**	**≥25**
Overall						
Herding	8.14***	8.85***	8.70***	8.14***	7.39***	7.92***
	(0.04)	(0.07)	(0.12)	(0.21)	(0.37)	(0.83)
Buy Herding	8.67***	9.75***	9.70***	8.90***	7.75***	6.66***
	(0.05)	(0.09)	(0.17)	(0.28)	(0.47)	(1.09)
Sell Herding	7.58***	7.78***	7.46***	7.11***	6.90***	9.39***
	(0.05)	(0.10)	(0.18)	(0.32	(0.59)	1.26)

Notes: Table 11 reports the results of herding measurements in Dutch PFs' foreign portfolios. Total, buy and sell herding measures are presented for all assets. The results are percentages; standard errors are in parentheses, and T-tests are two tailed. Three asterisks indicate statistical significance at 1% level. Source: DNB

Meanwhile, the weight of less risky assets (e.g., bonds) increases in the portfolio due to the reduced share of riskier assets (for e.g., equities), which inflates actual allocation over the strategic allocation of less risky assets in Dutch PF portfolios.

Typically, to reduce this gap, PFs must increase their risk by buying riskier assets and reducing their less risky positions to certain limits. However, the instability in the bear market has shaken PF managers' trust, even in their own private information, due to highly volatile market conditions. Both this shaken trust and the need to adjust their asset allocations drive them to

change their preferences. Therefore, they prefer to follow the herd in scaling down less risky holdings to avoid the risk of potentially bad outcomes resulting from trading against the peer group under highly instable market conditions. For this reason, herding values will likely swell with an increase in the number of active PFs trading a particular security in a given month. We searched for the explanation by quantifying herding measures for months in which more than two PFs actively traded a security, and the results are reported in Table11.

The overall average herding measure increases as the number of actively trading PFs for a security increases from two to ten and from 25 to higher. These results suggest that herding is more prevalent in securities where more PFs are active, a finding consistent with the studies of Grinblatts et al. (1995), Raddatz et al. (2008), Wylie (2005) and Voronkova et al. (2005).

3.6. Conclusion

This paper examines the investment behavior of institutional investors and provides evidence of high trading activity, feedback strategies and herding behavior in the trading patterns of Dutch PFs. We disproved the theory that all PFs are passive traders by finding that Dutch PFs display a monthly turnover rate of approximately 8.5%. We attribute these findings to a security's individual characteristics, such as liquidity and riskiness. The estimated values of regressions for the turnover measures of Grinblatts et al. (1995) and Ferson et al. (2002) show that turnover is explained in part by a PF's size and contemporaneous returns on equities. We found strong evidence for contrarian trading by Dutch PFs on an aggregate basis; however, it varies considerably across asset classes. Furthermore, we found that lag institutional demand for a security drive momentum investment in riskier assets and contrarian investment in less risky assets. A security's contemporaneous and lagged performance drive contrarian investments across asset classes.

In line with many earlier studies, we also applied Lakonishok, Shleifer and Vishny's (1992) measure to compute the average herding among Dutch PFs. Our results show robust evidence for herding among Dutch PFs, with an average herding of approximately 8.14%, and its presence becomes more obvious as a security's monthly trade increases above more than two active traders. Possible explanations for this trend include outsourcing of portfolio management and small PFs' imitation of large PFs' asset allocation strategies. We also observed herding asymmetry in the buying and selling of securities by Dutch PFs. Across asset classes, we found a higher degree of herding in less risky assets, and we suggest assets' liquidity as the explanation for lower herding in these assets.

Our results indicate that the recent financial turmoil has significantly affected the trading behavior of Dutch PFs. We observed higher turnover as well as increased herding during the crisis. Average herding was higher during the financial crisis but was largely driven by higher sell herding. A higher likelihood of performance based feedback trading was also observed during the crisis.

Chapter 4: Institutional Herding and Mutual Funds

This paper explores herding dynamics in the trading and investment behavior of US mutual funds and documents evidence of increased herding over time. We observe (slightly) higher levels of overall herding compared to the mainstream herding literature with asymmetry on the buy and the sell side; the overall herding level is weakly affected by scale economies and significantly influenced by a fund's style. Increased participation of mutual funds in the financial markets, proxied by the number of quarterly traded securities, appears to be positively correlated with mutual funds' herding. Both stocks' beta and market volatility are found to be crucial determinants of herding. A higher demand for smaller-sized stocks confirms the presence of the small-firm-effect anomaly. We find US mutual funds' herding more in bad market scenarios compared with good market environments.

4.1. Introduction

For the last two decades, the financial world has changed quite rapidly, as more problems have emerged for researchers studying the behavior of the financial markets and its determinants. During the last decade, we have witnessed two of the worst economic episodes, the dotcom bubble of 1999-2001 and the global financial crisis of 2007-2009. The global financial crisis has generally been considered the worst since the Great Depression of 1929 and has severely affected the major economies of the world, leading many previously strong institutions to default (e.g., Lehman Brothers, Bear Stearns, Merrill Lynch). Having eroded a substantial portion of the world's financial wealth, these crises have exposed the vulnerability of institutional investors to many significant risks[37] and forced financial analysts, professionals and academics to more carefully analyze both the potential micro and macro factors that may affect stock prices. One of these potential factors is the trading behavior of institutional investors.

Due to an enormous increase in their financial wealth over the last few decades[38], institutional traders have attracted the focus of academics and financial professionals; the relationship between institutional investments and stock prices has been of particular interest. Some of the main players among institutional traders are mutual funds (MFs). This growing industry has attracted more than 4 trillion US dollars by the end of 2007 [Glode,(2011)], with a tremendous compounded annual growth rate of 16% from 1980 to 2008 [Wahal et al. (2011)]. Because MFs compose a significant portion of institutional wealth, their trading behavior mimics the general investment behavior of institutional investors.

Price impact literature shows that institutional trading affects security prices – see, for instance, Grinblatt et al. (1995), Nofsinger et al. (2002), Wermers (2002), Sias (2004), Patterson et al. (2006), Puckett et al. (2008), Dasgupta et al. (2011) – but the direction of the effect is still not conclusive. Some studies document that institutional trading stabilizes security prices (Nofsingeret al. 2002, Wermers 2002, Sias 2004), while others advance the idea of a destabilizing effect of institutional trading on security prices (patterson et al. 2006, Puckett et al. 2009, Dasgupta et al. 2011). Most of these studies use feedback trading and herding as trading strategies to gauge the relationship between institutional trading and security price movements. Herding refers to any mass movement into (or out of) some specific stocks for whatever reason

[37] Including credit risks, liquidity risks, funding risks, stock market volatility, etc.
[38] Institutions account for about 64% of the market value of the CRSP (Dusgupta 2010).

[Falkenstein (2012)] and is a special case of feedback trading. Despite the perceptions of market watchers and herding theories, empirical evidence on herding is mixed; i.e., the evidence differs as to the documentation of the magnitude/level of herding across institutions and over time. For instance, Lakonishok et al. (1992) study US PFs quarterly data during the period 1984-1988 using feedback strategies in 769 US PFs and find an insignificant presence of herding. Their computed herding value is documented to be as little as 2.7 percent. Economically, this number translates as follows: if 100 MFs are active in the same security in the same month, then 2.7 more MFs are trading on the same side of the market than would be expected under the null hypothesis of random selection of securities. Grinblatt et al. (1995) investigate herding using quarterly data of 274 MFs' holdings over the period 1975-1984 and find economically insignificant levels of herding in US MFs, with a herding level reported to be 2.29 percent. Furthermore, these herding levels vary cross-sectionally across different styles of MFs. Wermers (2002) investigates herding and feedback strategies in US MFs over a relatively longer time span, from 1975 to 1994, and finds slightly higher herding levels, approximately 3.4 percent. His conclusion is consistent with the theory that institutional trading stabilizes security prices by concluding a speedy price-adjustment process spurred by institutional trades. More recently, Sias (2004) and Gutierrez &Pirinsky(2007) use different methodologies to find significant levels of herding in an average stock by US institutional investors. Compared with the older studies, Sias (2004) concludes that the use of different herding measures, rather than different sample periods, matters more in finding different herding levels in institutional investments. He measures herding over a longer sample period but does not consider the financial markets' high volatility periods in his conclusion. Recently, Patterson et al. (2006) investigate herding in institutional investors' trading behavior using quarterly frequency data over the turbulent period of 1999-2001 and find considerable herding in general and in technology stocks in particular. They also find herding asymmetry on the buy and the sell side and explain that institutional buy-herding destabilizes stock prices, but that institutional sell-herding helps adjust stock prices to their fundamentals. Though Patterson et al. (2006) attempt to explain the herding behavior of institutional investors during down markets, they restrict themselves to technology stocks only. The studies of Puckett et al. (2008) and Dusgupta et al. (2010) are also consistent with the idea of stronger herding in institutional trading. Though Sias (2004) offers a herding measure unaffected by the sample period of the data sample, the chronological comparison of these studies reveals changing quantitative levels (magnitude) of herding over time and across institutions. The extant studies - see, for instance, Lakonishok et al. (1992), Grinblatt et al. (1995), and Wermers (2002) – find a weak level of herding, while more recent studies [Patterson et al. (2006), Puckett et al. (2008) and Dasgupta et al. (2011)] document somewhat stronger levels. The studies that include recent periods in their data samples document slightly higher levels of mutual fund herding. Inclusion of a longer sample period and the implicit presence of financial turmoil in their data samples could be the driving force behind the higher levels of herding in their findings. Choe et al. (1999) document decreased herding and feedback trading during the Korean economic distress (1996-1997), while Hwang et al. (2004) find herding levels reduced during the Asian and Russian crises. Moreover, financial commentators have often claimed that herding has increased over time, but they have not yet found any empirical support for their claims.[39] These observations may be a starting point to explore interesting questions include whether incentives to herd co-move with market characteristics such as volatility.

MFs may have a comparative advantage in holding securities with certain characteristics so that when a security acquires these characteristics, its aggregate demand increases. Extant literature reports that certain characteristics of stocks drive MFs' demand, such as a non-linear preference for high-volatility stocks and an aversion to low-price stocks [Falkenstein (2012)], resulting in an increased demand for large and liquid stocks [Gompers and Metrick (1998], a tendency to hold growth stocks [Frazzini et al. (2008)], and a reduced desire for stocks with little information [Falkenstein (2012)]. The demand for a stock may change not only because of its idiosyncratic risk but also because of its correlation with market risk, i.e., a stock's beta. Studies documenting herding on a stock's beta seem nonexistent in the literature.

In summary, the existing literature on herding can be characterized into two clear strands. The first strand focuses on tracing the presence of herding in institutional trading behavior, and the second strand investigates the impact of institutional herding on stock prices. When exploring the presence of herding in institutional investment behavior, no study has specifically focused on the dynamics of herding and its determinants. We attempt to fill this gap by investigating whether market conditions, fund characteristics and stock characteristics can be determinants of increasing herding over time. With these objectives and considering the statements of financial commentators, changing herding levels over different sample periods, the trading behavior of MFs during market downturns and the non-exhaustive literature on stocks' characteristic herding, we raise some important questions to investigate: Do MFs' levels of herding change over time?

[39] Financial commentators and investors often say that herding in the financial markets is increasing (Vivek 2004).

Do herds emerge and become dominant in periods of substantial price movements? Do MFs limit themselves, in the long term, only to specific stocks?

We attempt to answer these questions and contribute to the existing literature in several ways. First, we investigate herding over time and provide empirical evidence of increased herding in the trading behavior of institutional investors. Second, we focus on mutual funds' styles, market capitalization, participation in the financial markets and market realized volatility as determinants of significant herding over time. Third, we analyze the herding behavior of MFs during both bull and bear markets to see whether herding in the trading behavior of MFs co-moves with market conditions. Last, we extend the existing literature on the characteristics of herding, for instance, stocks' sensitivity to market movements (beta). Because this chapter focuses on a detailed investigation of herding dynamics over time and its determinants, exploring the institutional herding effect on security prices is beyond the scope of this chapter and is left for the future research.

Using data comprising all stocks listed on the NYSE, NASDAQ and AMEX that were held in the portfolio holdings of US equity MFs over the period January 1980 to December 2009, we explore the herding dynamics in US MFs' trading and document the evidence of increased herding over time. We observe (slightly) higher levels of overall herding compared with the mainstream literature, with asymmetry on the buy and the sell side; the overall herding level is weakly affected by scale economies and significantly affected by funds' styles. Increased participation of MFs in the financial markets, proxied by quarterly traded securities, is positively correlated with quarterly average herding. Both a stock's beta and market volatility are found to be crucial determinants of herding. We find US MFs' herding more in bearish scenarios compared to bullish environments.

The remainder of this chapter is organized as follows: Section 2 explains the data. Section 3 describes our research design and methodology. In Section 4, empirical results are presented and Section 5 concludes.

4.2. Data and Descriptive Statistics

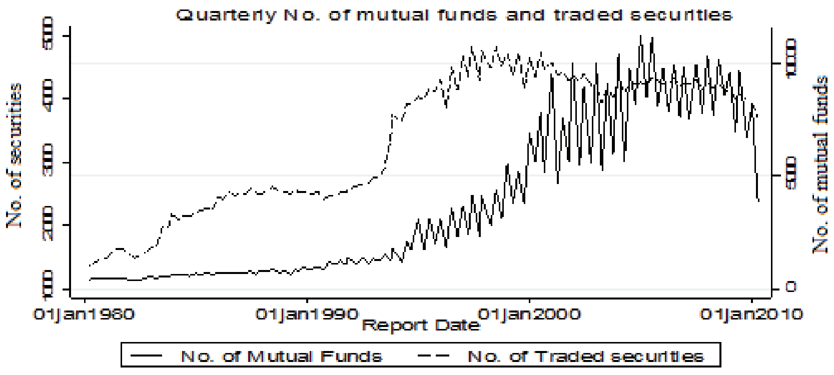
Most of the data for this research comes from Thomson Financial, formerly known as CDA/Spectrum, and has been used in many empirical studies, such as those by Grinblatt and

Titman (1989, 1993) and Wermers (1997, 2000, 2002). The database covers almost all historical domestic MFs plus approximately 3,000 global funds that hold a fraction of assets in stocks traded on US exchanges and well-known Canadian stock markets since 1980; the dataset is claimed to be largely free of survivor bias, as it includes all the equity funds over the known period [Carhart (2012)]. We restrict ourselves to domestic equity funds and classify them into growth, aggressive growth, growth & income, balanced and unclassified funds.[40] Regarding asset classes, MFs' holdings are determined through quarterly observations of both fixed income and equity holdings, but we choose to analyze only equities because we want to compare our results with previous studies as well. According to the Investment Company Act of 1940, US SEC requires all institutional investors with assets of more than $100 million under management to submit a report on detailed equity positions if their portfolio holdings contain more than 10,000 shares or amount to a market value of $20,000 within 60 to 90 days after the end of a calendar quarter. Thomson Financial makes appropriate adjustments for CUSIP changes, stock splits, and other stock distributions from the holdings data. Our dataset comprises asset positions, share prices (size), quarterly assets, changes in asset positions, purchases, sales and holding periods. We use the calendar quarter as the unit of time. To proxy the market realized volatility, we calculate the volatility of the S&P 500 Index as an indicator of good and bad market situations. We consider the good (bad) period to be proxied by a quarter in which volatility is low (high) and returns are higher (lower). Our sample comprises quarterly observations for firms listed on the NYSE, NASDAQ and AMEX over the period Jan. 1980 to Dec. 2009. We use daily price data from the CRSP to calculate quarterly abnormal returns and stocks' sensitivity to market risk (Beta).

Figure 6 shows the quarterly dynamics of the number of MFs and the number of securities traded by the MFs. We notice a high positive correlation between the number of active MFs and the number of securities they trade over time, implying that the more that MFs emerge in the markets, the higher the number of securities they explore for trading. The average number of stocks traded by MFs per quarter is approximately 30 (varying from 1,362 to 4,816), and the number of average active MFs per quarter is 560 (fluctuating from 404 to 11,220) over the sample period.

[40] User's Guide to Thomson Reuters.

Figure 6 Quarterly number of traded securities and number of mutual funds



Notes: Figure 6 reports the evolution of the number of mutual funds and the number of securities per quarter. Number of securities and number of mutual funds are on the Y-axis, and time span in the quarter is on the X-axis. Source: Thomson Financial/CDA-Spectrum

4.3. Research Design and Methodology

Our investigation commences with the computation of the Lakonishok et al. (1992) herding measure (*LSV*), which is defined as:

$$LSV_{i,t} = \left| \frac{B_{i,t}}{N_{i,t}} - P_t \right| - AF_{i,t} \quad (1)$$

Here, $LSV_{i,t}$ is the herding measure for *i*th security at time *t*, $B_{i,t}$ is the number of MFs buyers of *ith* security at time *t* and follows a binomial distribution with probability of success P_t, P_t is the expected number of buyers at time *t*, $N_{i,t}$ is the total number of active MFs for *ith* security at time *t* and $AF_{i,t}$ is the adjustment factor to allow for random variation around P_t under the null hypothesis of independent decisions by the MFs and is the expected value of $| B_{i,t}/(N_{i,t}) - P_t |$. The overall herding measure *LSV* is the average of $LSV_{i,t}$ over all securities and periods. A positive value of herding significant under the T-test will support the evidence of herding in MFs under the normality assumption. We also apply a filter to the sample data prior to computing *LSV,* i.e., two or more MFs must be active in a security quarter for the security to be included in the *LSV* calculation during that quarter.

One of our main objectives is to explore whether herding exhibits positive innovation over time; therefore, we run a time-series regression of time-effect on herding by using the *LSV* herding measure as the dependent variable as follows:

$$LSV_t = \beta_0 + \beta_1 T + \varepsilon_t \quad (2)$$

A positive effect of time on herding levels leads us to extend our investigation to the potential factors that play a part in positive innovation to herding levels over time. Some of these potential factors include the experience curve effect, increased participation of the MF industry, an increased number of securities traded by these MFs and increased market volatility over time. Usually, MFs hire sophisticated qualified professionals for their portfolio management who make use of increased financial knowledge and cutting-edge IT tools to quickly incorporate new information into security prices. The increasing use of state-of-the-art electronic commerce IT, easy access to financial information and enhanced exposure through investment operations add to portfolio managers' financial knowledge and investment skills over time. This learning-curve effect may lead portfolio managers to extract similar signals for the same security at the same time, and therefore, their herding level may increase over time. A lower number of available securities to trade in a certain quarter can limit the MFs' trading choices and may cause concentration of MFs. Alternatively, a higher number of active MFs in the financial markets may increase the competition to explore more profitable stocks and may add to the number of traded securities in a certain quarter. We find a high correlation between the quarterly number of participants in the mutual fund industry and the number of securities they trade, which leads us to analyze only one of these potential factors (see Appendix A). A final potential factor is the volatility of the market in which MFs operate. Some studies document that institutional trading affects security prices and in turn exacerbates market volatility (Gabaix and Gopikrishnan, 2006). We look at the alternative and assume that market volatility has an impact on managers' risk preferences and can explain mutual fund herding over time. We do not use regression models in our analysis; rather, we focus on a decile analysis of different factors to explore insights into the explanatory factors for herding.

Average herding does not communicate anything about whether herds are more on the buy or the sell side of the traded stocks. This phenomenon is documented as herding asymmetry and has been observed when institutions trade into and out of securities (Patterson et al. 2006). In addition to the variables affecting overall herding, herding asymmetry may also vary significantly over time. We follow Grinblatt et al. (1995) to discern between buy (BLSV) and sell (SLSV) sub-herding measures using the following equations:

$$BLSV_{i,t} = \left| \frac{B_{i,t}}{N_{i,t}} - P_t \right| - AF_{i,t} \quad \text{if} \quad \frac{B_{i,t}}{N_{i,t}} > P_t \qquad (4)$$

and $$SLSV_{i,t} = \left| \frac{B_{i,t}}{N_{i,t}} - P_t \right| - AF_{i,t} \quad \text{if} \quad \frac{B_{i,t}}{N_{i,t}} < P_t \qquad (5)$$

We replicate the above methodology to explore whether the above explained variables affect MFs' herding differently when trading into and out of securities over time.

Our period of investigation is long enough to encompass different macroeconomic environments, i.e., stock market booms, crashes, recoveries, recessions, and good and bad market situations. We take into account that the effect of realized market volatility on the trading behavior of US MFs may not be linear and can be higher during certain periods. Using returns and the volatility of the S&P 500 Index as a proxy for market returns and realized volatility, we segregate the realized quarterly volatility into ten deciles in order to investigate the general herding-volatility relationship. We also explore the herding behavior of MFs in particular cases, i.e., Black Monday (1987), the dotcom bubble (2000), the credit crisis (2007), and good and bad market conditions. To differentiate between good and bad market conditions, we sort the returns and the volatility of the S&P 500 Index into five quintiles and match them in reverse order to construct five portfolios. The extreme quintiles (the lower quintile of returns with the upper quintile of volatility and vice versa) are supposed to be crisis and boom periods, respectively. We define a market situation as bad (good) if it falls contemporaneously into the second (fourth) quintile of market returns and the fourth (second) quintile of market realized volatility. Last, the middle quintile is defined as a normal period.

Grinblatt et al. (1995) document that average herding varies across different styles of MFs. For instance, they find higher herding in growth funds and lower herding in balanced funds, which means that herding across MFs' styles may vary over time, i.e., over time, some MFs may herd more than others. We also investigate the anomaly of the small-firm effect in the trading behavior of MFs.

4.4. Empirical Results

4.4.1. Does Herding Increase Over Time?

We begin our analysis by computing the LSV herding measure over the analysis period; Table 12 shows the results of our LSV herding measures over time. In Panel A of Table 12, we observe a slightly higher level of average overall herding, approximately 5.75%, compared with prior studies on US MFs.

Table 12 Mutual Funds' herding over time

Panel A	Overall	Buy	Sell
Overall (1980-2009)	5.748	4.836	7.383
	(0.020)	(0.017)	(0.046)
Panel B	**5-years Span**		
1980-1985	4.333	2.480	6.960
	(0.071)	(0.055)	(0.150)
1986-1990	4.873	3.684	6.432
	(0.056)	(0.049)	(0.112)
1991-1995	5.408	3.720	8.320
	(0.043)	(0.033)	(0.099)
1996-2000	5.654	3.880	8.792
	(0.044)	(0.032)	(0.104)
2001-2005	6.349	6.170	6.795
	(0.041)	(0.036)	(0.114)
2006-2009	7.407	7.781	6.682
	(0.057)	(0.057)	(0.126)
Panel C	**10-years Span**		
1980-1990	4.660	3.199	6.635
	(0.044)	(0.037)	(0.090)
1991-2000	5.528	3.799	8.550
	(0.030)	(0.023)	(0.072)
2001-2009	6.755	6.861	6.513
	(0.032)	(0.030)	(0.079)

Notes: Table 12 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. Overall, buy and sell herding measures are presented for different time periods. The results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are statistically significant at 1% level.
Source: Thomson Financial/CDA-Spectrum

Economically, this number translates as follows: if 100 MFs are active in the same security in the same month, then 5.75 more MFs are trading on the same side of the market than would be expected under the null hypothesis of random selection of securities. The LSV herding measures are averaged over time and securities; Panel B and C in Table 12 further highlight that herding levels consistently increase even at five-year and ten-year time spans. The overall average herding measure is characterized by sell-herding, i.e., sell-herding is stronger than buy-herding, which is consistent with Grinblatt et al. (1995) but inconsistent with the findings of Wylie (2005). We observe that in general, average herding in later time periods is on average higher than herding in earlier time periods. More importantly, the rate of increase is higher during more recent periods. A significantly positive effect of time on the LSV herding measure tends to support the hypothesis of increased herding over time in the investment behavior of US MFs.

Table 13 Mutual Funds' herding across different styles

Panel A	Aggressive Growth	Growth	Growth & Income	Balanced	Unclassified
overall herding	4.304	5.208	5.817	6.707	9.775
	(0.692)	(0.023)	(0.037)	(0.043)	(0.047)
buy herding	-1.532	4.284	5.184	5.297	6.634
	(0.421)	(0.021)	(0.036)	(0.042)	(0.035)
sell herding	16.145	6.56	6.855	8.723	16.017
	(1.72)	(0.047)	(0.078)	(0.085)	(0.115)
Panel B	**Regression results of fund styles' herding on overall herding**				
Beta	0.137	0.595	0.284	0.089	0.173
R2	0.0434	0.409	0.178	0.036	0.234
Adj. R2	0.0354	0.404	0.172	0.028	0.226

Notes: Table 13 reports the results of the LSV average herding measures at the overall, buy and sell sub-group levels for different styles of US mutual funds. Overall, buy and sell average herding measures are presented for different styles of MFs classified based on their objective codes. Panel A shows the average herding across different styles and the results are in percentages. Panel B exhibits the regression results of average quarterly herding of each style of MFs on overall quarterly average herding levels. Standard errors are in parentheses and T-tests are two-tailed. Three asterisks indicate statistical significance at the 1% level.
Source: Thomson Financial/CDA-Spectrum

This observation leads us to explore the determinants of increased herding in MFs' long term investment behavior; therefore, we focus on funds' expertise in true information extraction through experienced trading, MFs' characteristics (style, size)[41], increased participation of MFs in the funds industry and market realized volatility as some of the potential factors driving increased levels of herding in MFs' long term investment behavior. The longer the time horizon of the investment operations of a mutual fund, the more investment experience the mutual fund managers attain and, in turn, the higher the expected herding because different experienced MF managers are expected to make the same decisions at the same time by inferring the same

[41] As per the User's Guide by Thomson Reuters.

information from the signals from the same security. Due to the non-availability of the data, we leave this issue for future research.

Grinblatts et al. (1995) document slightly different levels of herding across MFs' styles. We extend our analysis to investigate whether funds' styles explain increased average herding over time. Following Grinblatts et al. (1995), we first attempt to calculate whether herding levels are significantly different across MFs' classifications, and then we extend our investigation to explore whether the herding contributions of some of these styles to the overall herding over time is higher compared with other styles. The results for the average LSV herding measures for each style are presented in Panel A of Table 13.

We find that herding level differs significantly across different styles of MFs classified on the basis of their objective codes. We find aggressive growth MFs experience the minimum and unclassified MFs bear the maximum average herding levels. Though unclassified MFs' trading exposes the highest average herding levels across different styles of the MFs, the growth and growth & income MFs are dominant in terms of market capitalization and numbers in our data. This observation leads us to investigate the amount each group contributes to the overall average herding. We calculate quarterly herding across mutual fund styles and regress it using overall quarterly average herding as the dependent variable. The results are illustrated in Panel B of Table 13. We observe that though unclassified MFs herd most, growth MFs lead. Balanced MFs are the least in terms of effect and explanation for overall herding. The results also show that the investment behavior of the growth MFs appears to be the major driver of increased herding over time in US MFs' investment behavior.

Prior studies document the diseconomies of scale [Perold (1991)] concerning the trading costs of US MFs, yet, in absolute terms, large MFs bear more trading costs[42] compared with small MFs. Funds with low capitalizations may require greater search costs to explore desirable securities for their portfolios. Because firm size proxies the amount of information and the number of professional analysts that process the available information about an enterprise [Collins (1987)], the size of a MF has the potential to affect herding in the sense that a large mutual fund has the ability to bear a higher absolute cost for information collection and security analysis. A large MF

[42]Actively managed funds incur substantially higher trading costs than index funds (Wermers 2000).

can hire smart managers for this purpose; if some of the large funds' smart managers pick up the same security for analysis at the same time, they may infer the same signals on the basis of their expert information. Thus, on one hand, inferring the same information may induce large MFs to trade the same security at the same time and in the same direction; on the other hand, small MFs may mimic the profitable strategies of the large funds to reduce their cost of information collection and thus cause a higher LSV herding measure. To investigate the validity of this theory, we sort all the MFs into ten deciles each quarter on the basis of their quarterly equity holdings and calculate their LSV herding measures. Table 14 presents the average LSV herding results for each decile. Though insignificant values of the F-test do not support convincing evidence for this theory, there is weak evidence against it when we move from the lowest size decile to the highest size decile. In fact, we observe significant herding in all deciles; however, the average herding measure does not change significantly across all deciles. We find comparatively higher levels of herding in extreme deciles (and significant values of the F-test show that average herding changes across deciles).

Table 14 Mutual Funds' herding across fund-size deciles

Panel A	Lowest	2	3	4	5	6	7	8	9	Highest
Overall	5.685	4.917	5.743	4.738	4.859	5.731	4.907	5.285	5.361	5.57
	(0.035)	(0.033)	(0.034)	(0.032)	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)
buy	2.833	2.557	3.552	2.675	3.159	3.448	3.045	3.335	3.812	3.639
	(0.026)	(0.025)	(0.027)	(0.027)	(0.026)	(0.026)	(0.026)	(0.027)	(0.028)	(0.026)
sell	10.498	8.998	9.154	7.889	7.472	9.242	7.787	8.182	7.613	8.611
	(0.081)	(0.076)	(0.074)	(0.069)	(0.068)	(0.071)	(0.069)	(0.07)	(0.066)	(0.072)
Panel B	**Regression results of fund-size herding on overall herding**									
coeff.	0.166	0.232	0.14	0.165	0.094	0.155	0.252	0.231	0.27	0.171
R2	0.088	0.127	0.076	0.076	0.032	0.103	0.184	0.157	0.236	0.136
Adj. R2	0.08	0.12	0.068	0.068	0.024	0.095	0.178	0.15	0.229	0.129

Notes: Table 14 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. In Panel A, overall, buy and sell herding measures are presented for fund-size deciles, where deciles are created on the basis of the quarterly total assets each mutual fund holds. The first decile shows the minimum/lowest 10%, and the last decile presents the upper 10% of funds' capitalizations. Panel B exhibits the regression results of the average quarterly herding for each decile of MF sizes on the overall quarterly average herding levels. Panel A's results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are significant at the 1% level.
Source: Thomson Financial/CDA-Spectrum

The comparatively higher levels of herding in smaller-sized MFs can be attributed to the fact that small MFs mimic the trading strategies of large MFs, while the comparatively high levels of herding in higher deciles may be information-based. We also run a regression of the size-decile herding on overall herding to explore whether particular size-deciles explain most of the overall herding. Panel B of Table 14 presents the regression results; it is clear that higher-size deciles affect the overall herding most. A higher R^2 for large MFs indicates that the herding behavior of large MFs explains most of the overall average quarterly herding. We also find herding asymmetry across the fund-size deciles' herding, with large MFs herding more on the buy side and small MFs herding more on the sell side.

4.4.2. Do herds emerge and become dominant in times of high price movements?

Market volatility is observed to be non-constant and varying over time (Campbell (2001), and some studies [Choe et al. (1999), patterson et al. (2006)] implicitly indicate a possible relationship between market volatility and LSV herding measures. We also observe herding levels changing over time (see Table 12). This observation leads us to suspect that market volatility may affect the incentives for US MFs to herd. In an attempt to explore the empirical evidence for a relationship between stock market realized volatility and MFs' herding behavior, we classify quarterly market realized volatility into ten deciles and calculate herding for each decile.[43] The results are documented in Table 15. We observe unclear patterns of LSV herding across the volatility deciles; however, average herding in the upper deciles of market realized volatilities is slightly higher than in the lower deciles. We also observe a dominating pattern, in general, for sell-herding over buy-herding in the higher volatility deciles. In general, our results are inconsistent with studies [Choe et al. (1999), Lobao (2002)] that document that herding decreases in bad market periods. Our results are also inconsistent with Hwang et al. (2004), who find reduced herding during the Asian and Russian crises, and Christie et al. (1995), who do not find significant herding during down markets. However, higher buy-herding during down market periods and higher sell-herding during market downturns is consistent with the findings of Choe et al. (1999).

Panel B of Table 12 also shows that the herding increment seems to be higher in time periods involving any crisis episode – see, for instance, the dates of Black Monday in 1987, the dotcom crisis (2000-2002) and the recent credit crisis (2007) - which suggests the possibility of a significant shift in MFs' trading behavior during these specific events. This observation leads us to investigate the herding patterns in investment behavior of US MFs during periods of market turmoil. The results presented in Panel B of Table 16 show significantly higher herding during

[43] The quarterly volatility of the S&P 500 Index has been used as a proxy for market volatility.

periods of market turmoil than during non-turmoil periods. We further extend our analysis to investigate herding in US MFs' trading behavior during important crisis periods; Panel A of Table 16 reveals herding during the different crisis periods in our sample. Again, we observe a chronological increase in MFs' herding behavior.

Table 15 Mutual Funds' herding across realized market volatility deciles

Herding	Lowest	2	3	4	5	6	7	8	9	Highest
Overall	5.62	5.952	6.605	6.039	5.354	5.161	6.014	5.703	7.359	5.803
	(0.071)	(0.071)	(0.077)	(0.072)	(0.078)	(0.073)	(0.077)	(0.074)	(0.082)	(0.082)
Buy	6.333	6.011	5.717	5.023	4.564	4.421	5.494	3.912	6.059	5.043
	(0.07)	(0.064)	(0.067)	(0.062)	(0.069)	(0.059)	(0.069)	(0.052)	(0.071)	(0.071)
Sell	4.06	5.797	8.277	7.785	6.506	6.629	6.858	8.917	9.528	7.117
	(0.166)	(0.194)	(0.182)	(0.164)	(0.161)	(0.182)	(0.168)	(0.179)	(0.183)	(0.186)

Notes: Table 4 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. Overall, buy and sell herding measures are presented for stock market volatility deciles where the deciles are constructed by sorting the quarterly stock market volatility, proxied by the volatility of the S&P 500 Index, into ten equal parts over the observation period. The first decile shows the lowest 10%, and the last decile presents the upper 10% of the 120 quarterly market volatility observations. The results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are significant at the 1% level. Source: Thomson Financial/CDA-Spectrum

We observe that herding during the global credit crisis (2007) was much higher compared with other crisis periods. The major reason for this higher scale of herding during the credit crisis (2007) seems to be the dissemination of the crisis to all types of stocks, while a comparatively low level of herding during the Black Monday crisis (1987) is a result of crisis exposure that was mainly limited to certain stock indices.

We also investigate the herding behavior of US MFs in good and bad market conditions (as defined above) and observe much higher levels of herding during bad environments compared with good market conditions. We find herding levels in bad market conditions to be at least 2 percent higher than in good environments. However, this higher level of herding is mainly characterized by sell-herding. Higher buy-herding levels than sell-herding levels in bad market conditions is inconsistent with the findings of Choe et al. (1999).

Table 16 Average herding measures by stock market conditions

Panel A. By crisis	Overall	Buy	Sell
Black Monday Oct 1987-Dec 1988	3.216	3.929	2.403
	(0.199)	(0.195)	(0.362)
Dotcom Bubble Mar 2000-Oct 2002	6.219	4.985	8.693
	(0.055)	(0.041)	(0.141)
Credit Crisis Sep 2007- Dec 2009	7.407	7.781	6.682
	(0.057)	(0.057)	(0.126)
Panel B. Crisis vs. Non-crisis			
During crisis (overall)	6.643	6.283	7.333
	(0.039)	(0.035	(0.092)
During non-crisis (overall)	5.433	4.310	7.399
	(0.023)	(0.019)	(0.053)
Panel C. Bad and Good Market Periods			
Bad Market Periods	8.069	8.089	8.024
	(0.140)	(0.125)	(0.362)
Good Market Periods	5.923	4.185	8.444
	(0.148)	(0.118)	(0.316)

Notes: Table 16 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. Overall, buy and sell herding measures are presented for different time environments of the market. Crises are important historical stock market crashes. Bear and bull market conditions are constructed on the basis of returns and volatility quintiles (5) of the S&P 500 Index. The results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are statistically significant at the 1% level.
Source: Thomson Financial/CDA-Spectrum

4.4.3. Does MFs' demand for stock hinge on the stock's characteristics?

Over time, increased participation of MFs in the financial markets and their trading of an increasing number of securities has been observed (see Appendix A and Figure 1), which implies that when more MFs trade in the stock market, they investigate and trade more stocks. Increased active trading or increased participation of MFs in the security market may decrease the chances of higher herding in some of the traded securities and, similarly, a higher number of available securities to trade may hamper the concentration of MFs in certain stocks because they have more choices among available securities to include in their portfolios. To investigate whether increased participation of MFs in the financial markets affects their herding levels, we sort the number of quarterly traded securities, a proxy for increased participation of MFs, over time into ten deciles and calculate the LSV herding measure for each of the deciles; the results are shown in Table 17. To our surprise, we find increased levels of herding in general, though non-monotonic, as we move from the lower decile of the number of securities to the higher decile.

Table17 Mutual Funds' herding across security-count deciles

Herding	Lowest	2	3	4	5	6	7	8	9	Highest
Overall	3.946	4.06	4.657	3.949	6.467	6.921	6.519	7.023	6.804	5.53
	(0.182)	(0.181)	(0.184)	(0.187)	(0.194)	(0.178)	(0.189)	(0.177)	(0.194)	(0.192)
Buy	2.204	1.681	2.157	2.448	4.734	4.734	4.155	4.016	3.088	1.538
	(0.124)	(0.114)	(0.121)	(0.128)	(0.149)	(0.125)	(0.126)	(0.11)	(0.12)	(0.096)
Sell	6.629	8.035	8.251	5.946	9.92	12.053	11.63	14.059	15.634	17.654
	(0.417)	(0.433)	(0.403)	(0.398)	(0.49)	(0.5)	(0.512)	(0.498)	(0.536)	(0.623)

Notes: Table 17 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. Overall, buy and sell herding measures are presented for the number of traded securities per quarter by sorting them into 10 deciles. The first decile shows the minimum 10% of the number of quarterly traded securities, and the last decile shows the maximum 10% of the number of quarterly traded securities. The results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are significant at the 1% level.
Source: Thomson Financial/CDA-Spectrum

Appendix A shows a high positive correlation between the number of MFs participating in the financial markets over time and the number of securities they trade. The presence of more tradable securities in the financial markets may hamper the concentration of US MFs in certain securities. Our results show that this is not the case; an increased number of listed securities in the financial markets over time does not affect the choices of MFs, and the MFs remain concentrated in certain stocks. Though the participation of MFs in the financial markets increases over time, their concentration converges on certain desired securities. It seems that new entrants follow the old ones in certain stocks, which eventually adds to the average overall herding levels over time. This finding raises another important question: is there a relationship between security characteristics and increased herding? To identify this link, we focus on risk and the stock-size preferences of the MFs for the concentrating characteristics of the securities. Taking share size, we sort all stocks into ten deciles each quarter and calculate the average LSV herding measure for each decile. The results are shown in Table 18. We find an asymmetric relationship between the average herding measure and the stock-size deciles. Panel A of Table 18 shows a nonlinear demand for stock-size deciles, i.e., the LSV herding measure increases as we move from the middle to the extremes of the stock-size deciles. High demand for large stocks is consistent with the findings of Gompers and Metrick (1998), but the higher demand for smaller-sized stocks is inconsistent with the findings of Falkenstein (2012), who finds an increasing aversion of funds for low-priced holdings. The general results in Panel A of Table 18 show that US MFs have a much higher demand for stocks in the extreme deciles, especially at the lower end, but the results do not explain which share-size decile accounts for most of the overall herding over time. To address this issue, we run regressions of each share-size decile's herding on the overall herding; the results are presented in Panel B of Table 18.

Table 18 Mutual Funds' herding across stock-size deciles

Panel A	Lowest	2	3	4	5	6	7	8	9	Highest
Overall	5.738	4.329	3.871	3.554	3.503	3.536	3.525	3.742	4.204	5.188
	(0.038)	(0.04)	(0.043)	(0.044)	(0.046)	(0.05)	(0.055)	(0.061)	(0.072)	(0.085)
Buy	2.217	2.689	2.864	2.874	3.24	3.292	3.472	3.952	4.558	5.791
	(0.025)	(0.032)	(0.037)	(0.041)	(0.044)	(0.048)	(0.054)	(0.06)	(0.072)	(0.087)
Sell	11.493	6.802	5.399	4.575	3.905	3.926	3.608	3.396	3.603	4.037
	(0.087)	(0.087)	(0.09)	(0.092)	(0.096)	(0.103)	(0.112)	(0.127)	(0.15)	(0.182)
Panel B	**Regression results of stock-size herding on overall herding**									
Coeff.	0.703	0.842	0.994	1.053	0.925	0.852	0.714	0.656	0.545	0.641
R2	0.726	0.576	0.448	0.557	0.397	0.355	0.323	0.302	0.282	0.442
Adj. R2	0.723	0.572	0.444	0.553	0.392	0.349	0.318	0.296	0.276	0.437

Notes: Table 18 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. In Panel A, overall, buy and sell herding measures are presented for stock-size (stock price) deciles, where the deciles are constructed by sorting the prices of traded securities into 10 deciles each quarter. The first decile shows the lowest 10%, and the last decile shows the upper 10% of the stocks' prices each quarter. Panel B shows the regression results of the average quarterly herding of each decile of stock size on overall quarterly average herding levels. Panel A's results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are significant at the 1% level.
Source: Thomson Financial/CDA-Spectrum

Our results further confirm that smaller-sized stocks affect and explain most of the overall quarterly average herding; thus, the small-firm effect exists. We further note a systematic increase (decrease) of buy- (sell-) herding as we move from the low (high) to the higher- (lower-) sized decile. This finding is consistent with Gompers and Metrick (1998) and Falkenstein (2012) in documenting that MFs focus more on holding large stocks. Our results may lead us to conclude that although US MFs' demand for large stocks increases over time, they herd most in lower-sized stocks.

We further investigate whether large MFs have the same demand for large stocks as small MFs. For this purpose, we sort all MFs into five quantiles each quarter and then resort each size quantile into five share-size quantiles. We calculate the quarterly average herding of each of the twenty-five quantiles each quarter; the results are shown in Table 19. Our results in Panel A of Table 19 show that the average LSV herding across size quantiles does not change much, but that in general, both large and small MFs herd the most in the lowest capitalization stocks. When we look at the differences between the buy and sell LSV herding measures, the measures decrease from the lowest stock-size quantile to the highest stock-size quantile; the difference decreases most rapidly in the highest fund-size quantile. This observation shows an increasing (decreasing) demand (aversion) for (to) large (small) stocks for all MFs; however, the largest MFs show the highest demand for and the lowest aversion to the largest stocks. In general, we find that MFs herd most in the smaller-sized stocks, but this herding is mainly characterized by the highest aversion to and the least demand for small stocks. Over time, all MFs demand more large stocks; however, this tendency is most prominent in the largest MFs.

We also investigate if increased herding over time in the trading behavior of US MFs is due to a change in their risk preferences over time; therefore, we calculate stocks' betas for each of the holdings of MFs over the sample period using the CRSP database, and then we sort the stocks' betas into ten deciles.

Table 19 LSV herding measures for share-size and fund-size quantiles

Panel A			**Overall Herding** **Fund-Size Quants**		
Share-Size Quants	**Smallest**	**2**	**3**	**4**	**Largest**
Smallest	4.503	4.668	4.589	4.526	5.269
	(0.054)	(0.052)	(0.049)	(0.050)	(0.049)
2	3.609	3.632	3.770	3.585	3.872
	(0.052)	(0.051)	(0.049)	(0.049)	(0.051)
3	3.365	3.293	3.534	3.195	3.518
	(0.054)	(0.053)	(0.052)	(0.052)	(0.053)
4	3.537	3.317	3.435	3.119	3.511
	(0.059)	(0.059)	(0.058)	(0.058)	(0.059)
Largest	4.129	3.780	3.895	3.506	4.081
	(0.071)	(0.070)	(0.072)	(0.070)	(0.073)
Panel B			**Buy-Herding**		
Smallest	0.373	1.135	1.236	1.202	1.796
	(0.033)	(0.036)	(0.033)	(0.034)	(0.034)
2	1.405	1.839	2.139	2.040	2.577
	(0.040)	(0.042)	(0.041)	(0.041)	(0.043)
3	1.991	2.204	2.565	2.336	2.943
	(0.046)	(0.048)	(0.048)	(0.048)	(0.051)
4	2.820	2.710	3.000	2.636	3.421
	(0.055)	(0.057)	(0.056)	(0.057)	(0.061)
Largest	3.971	3.832	3.769	3.421	4.285
	(0.071)	(0.073)	(0.073)	(0.074)	(0.078)
Panel C			**Sell-Herding**		
Smallest	11.745	9.977	9.699	9.808	10.788
	(0.126)	(0.113)	(0.108)	(0.111)	(0.109)
2	7.049	6.073	6.079	5.775	5.755
	(0.114)	(0.105)	(0.102)	(0.103)	(0.106)
3	5.416	4.780	4.860	4.339	4.311
	(0.113)	(0.105)	(0.105)	(0.101)	(0.105)
4	4.592	4.156	4.068	3.763	3.632
	(0.121)	(0.116)	(0.116)	(0.110)	(0.112)
Largest	4.378	3.710	4.079	3.623	3.805
	(0.145)	(0.136)	(0.141)	(0.132)	(0.134)

Notes: Table 19 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. Overall, buy and sell herding measures are presented for stocks' betas in combination with fund size. The beta for each stock traded by US MFs has been calculated using EVENTUS, which uses the CRSP database to find stocks' betas. After calculating the quarterly betas of the stocks, they are sorted into five quantiles each quarter. The quantile with the smallest 20% of betas is called the lowest quant and the quantile with the largest 20% of betas is called the highest quant. A similar distribution has been made for the fund size. The results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are statistically significant at the 1% level.
Source: Thomson Financial/CDA-Spectrum

We also investigate if increased herding over time in the trading behavior of US MFs is due to a change in their risk preferences over time; therefore, we calculate stocks' betas for each of the holdings of MFs over the sample period using the CRSP database, and then we sort the stocks' betas into ten deciles.

Table 20 Mutual Funds' herding across stocks' beta deciles

Panel A	Lowest	2	3	4	5	6	7	8	9	highest
Overall	6.053	5.058	4.817	4.638	4.602	4.573	4.515	4.559	4.685	5.337
	(0.048)	(0.049)	(0.049)	(0.048)	(0.048)	(0.047)	(0.045)	(0.045)	(0.045)	(0.048)
Buy	4.930	4.335	4.195	4.158	4.253	4.268	4.359	4.429	4.675	5.300
	(0.040)	(0.045)	(0.046)	(0.046)	(0.047)	(0.046)	(0.045)	(0.044)	(0.044)	(0.044)
Sell	8.007	6.166	5.740	5.367	5.125	5.055	4.770	4.783	4.703	5.415
	(0.109)	(0.103)	(0.101)	(0.098)	(0.097)	(0.098)	(0.095)	(0.097)	(0.101)	(0.117)
Panel B	**Regression results of stocks' beta-herding on overall herding**									
coeff.	0.737	0.874	0.900	0.967	0.937	0.988	0.929	0.822	0.823	0.686
R2	0.816	0.731	0.659	0.538	0.503	0.549	0.517	0.449	0.409	0.443
Adj. R2	0.814	0.729	0.656	0.534	0.499	0.545	0.513	0.444	0.404	0.438

Notes: Table 20 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. In Panel A, overall, buy and sell herding measures are presented for 10 deciles of stocks' betas, where the deciles are constructed by sorting all stocks' betas into 10 deciles each quarter. The first decile shows the lowest 10%, and the last decile shows the upper 10% of the stocks' betas each quarter. Panel B shows the regression results of the average quarterly herding of each decile of stock's beta on the overall quarterly average herding levels. Panel A's results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are significant at the 1% level.
Source: Thomson Financial/CDA-Spectrum

We repeat this process each quarter; the results of the LSV herding measure for all ten deciles, averaged over time and securities, are shown in Panel A of Table 20. Our results strongly endorse the idea that US MFs herd most in low-beta stocks. Furthermore, their herding increases (though not monotonically) as we move from the higher to the lower-beta stocks. The noticeable result is that the difference between buy and sell-herding decreases in beta, i.e., over time US MFs herd more into (out of) the higher- (lower-) beta stocks. In other words, US MFs converge on the high-beta stocks in the long term. This observation shows that US MFs have some preferences for low-beta stocks in their long-term trading behavior.

They herd more in the stocks that do not change as much with the market. Panel B of Table 20 shows the regression results of each beta decile's quarterly herding on the overall average herding. The results further support the hypothesis that over time US MFs are more inclined toward stocks that have little correlation with market conditions. In other words, in the long term, the lowest-beta stocks attract the most MFs, but this result is mainly driven by herding out of these stocks.

In an attempt to explore whether the demand across stocks' riskiness changes with fund size, we first sort all the sampled MFs into five size quantiles, and then we sort each size quantile further into five beta quantiles. We repeat this process each quarter and then calculate the herding measures for each of the 25 sub-groups. The results are presented in Table 21. Consistent with the findings from Table 20, all types of MFs show the highest herding in the lowest-beta stocks; however, the demand for the lowest-beta stocks is the highest in the largest fund-size quantile. From Panel A of Table 21, we observe that all fund-size quantiles have a tendency to herd most in the lowest-beta quantile; however, the difference in average overall herding between the largest and the smallest beta quantiles is highest for the largest size quantile. Panel B and C of Table 21 suggest that the largest MFs herd most when buying the largest beta stocks. This finding endorses our hypothesis that large MFs hire sophisticated asset managers who end up trading the same securities at the same time in the same direction after their evaluations.

Table 21 LSV herding measure for fund-size and beta quantiles

Panel A			Overall Herding		
			Beta Quants		
Fund-size Quants	Smallest	2	3	4	Largest
Smallest	6.179	5.865	6.000	5.673	5.500
	(0.086)	(0.085)	(0.085)	(0.083)	(0.081)
2	6.356	6.086	5.826	5.790	5.527
	(0.084)	(0.083)	(0.081)	(0.080)	(0.079)
3	6.906	6.365	6.183	6.073	5.968
	(0.081)	(0.083)	(0.081)	(0.080)	(0.080)
4	6.226	6.060	5.873	5.656	5.606
	(0.080)	(0.081)	(0.080)	(0.078)	(0.077)
Largest	7.234	6.376	6.308	6.220	6.227
	(0.077)	(0.080)	(0.079)	(0.078)	(0.079)
Panel B			**Buy-Herding**		
Smallest	2.293	2.810	3.150	2.785	2.654
	(0.057)	(0.061)	(0.063)	(0.062)	(0.060)
2	3.330	3.529	3.608	3.664	3.368
	(0.060)	(0.064)	(0.065)	(0.064)	(0.064)
3	3.466	3.570	3.736	3.727	3.800
	(0.058)	(0.062)	(0.064)	(0.063)	(0.063)
4	3.262	3.446	3.606	3.471	3.595
	(0.057)	(0.063)	(0.063)	(0.062)	(0.063)
Largest	4.363	4.221	4.485	4.496	4.456
	(0.059)	(0.065)	(0.066)	(0.067)	(0.067)
Panel C			**Sell-Herding**		
Smallest	13.531	11.044	10.749	10.392	10.074
	(0.210)	(0.194)	(0.192)	(0.187)	(0.181)
2	11.272	9.967	9.208	8.924	8.743
	(0.190)	(0.180)	(0.176)	(0.171)	(0.168)
3	12.541	10.559	9.809	9.562	9.123
	(0.183)	(0.180)	(0.173)	(0.172)	(0.170)
4	11.251	10.078	9.309	9.001	8.633
	(0.185)	(0.175)	(0.172)	(0.169)	(0.164)
Largest	12.059	9.718	9.053	8.783	8.859
	(0.173)	(0.174)	(0.168)	(0.164)	(0.166)

Notes: Table 21 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. Overall, buy and sell herding measures are presented for stocks' betas in combination with fund size. The beta for each stock traded by US MFs has been calculated using EVENTUS, which uses the CRSP database to find stocks' betas. Quarterly betas of the stocks are sorted into five quantiles each quarter. The quantile with the smallest 20% of betas is called the lowest quant, and the quantile with the largest 20% of betas is called the highest quant. Similar distributions have been made for the fund sizes. The results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are statistically significant at the 1% level.
Source: Thomson Financial/CDA-Spectrum

Our study also investigates MFs' herding behavior in interaction with market conditions and stocks' betas. Table 22 shows the summary results of MFs' herding for the lowest and the highest stock-beta quants under different market conditions.

Panel A of Table 22 shows that overall herding does not change much for negative- and positive-beta stocks, but the demand (aversion) for (to) positive- (negative-) beta stocks is significantly higher (lower) than the negative-beta stocks over the course of investigation. Panel B of Table 22 presents the herding in different stock-beta quants vis-à-vis market conditions. We find that US mutual funds herd slightly more in positive-beta stocks during bull markets, which are mainly characterized by herding in the highest-beta stocks. Furthermore, average herding is slightly higher for the highest-beta quants in bear markets.

Table 22 Herding and Mutual Funds' Risk Preferences

Herding	Overall	Buy	Sell	Overall	Buy	Sell
Panel A		**Negative Stocks' Beta**			**Positive Stocks' Beta**	
	4.471	-0.012	14.115	4.059	1.722	8.321
	(0.091)	(0.072)	(0.210)	(0.022)	(0.020)	(0.048)
Panel B: Beta Quant		**Bear Markets**			**Bull Markets**	
Lowest	3.923	1.351	10.175	3.827	1.274	10.538
	(0.336)	(0.295)	(0.839)	(0.263)	(0.236)	(0.676)
Highest	5.172	4.257	7.364	4.737	3.092	8.627
	(0.443)	(0.404)	(1.139)	(0.320)	(0.306)	(0.772)
Negative Beta	3.631	1.101	11.679	-3.670	-0.011	14.066
	(0.607)	(0.501)	(1.805)	(0.423)	(0.348)	(1.114)
Positive Beta	3.936	2.757	6.402	4.328	2.659	7.682
	(0.136)	(0.129)	(0.317)	(0.112)	(0.110)	(0.247)
Panel C: Beta Quant		**Overall Crisis Periods**			**Overall non-Crisis Periods**	
Lowest	5.600	2.907	10.520	3.844	-0.351	12.705
	(0.109)	(0.105)	(0.230)	(0.062)	(0.050)	(0.143)
Highest	5.044	5.150	4.783	4.315	2.228	9.055
	(0.112)	(0.114)	(0.271)	(0.071)	(0.063)	(0.176)
Panel D: Beta Quant		**Black Monday Crisis (1987)**			**Dotcom Crisis (2000-2002)**	
Lowest	2.639	-1.661	9.480	5.862	1.313	13.622
	(0.264)	(0.235)	(0.521)	(0.187)	(0.148)	(0.394)
Highest	2.082	-0.442	6.001	6.478	6.369	6.926
	(0.353)	(0.347)	(0.693)	(0.176)	(0.158)	(0.624)
		Global Credit Crisis (2007-2009)				
Lowest	6.637	5.933	8.088			
	(0.154)	(0.165)	(0.323)			
Highest	5.025	5.917	3.137			
	(0.143)	(0.164)	(0.276)			

Notes: Table 22 reports the results of the LSV herding measures at the overall, buy and sell sub-group levels. Overall, buy and sell herding measures are shown for stocks' betas in combination with different market conditions. Betas for each stock traded by US mutual funds have been calculated using EVENTUS, which uses the CRSP database to find quarterly stocks' betas. After calculating the quarterly betas of the stocks, we sort all the betas into five quantiles each quarter. The quantile with the lowest 20% of betas is called the lowest quant and the quantile with the highest 20% of betas is called the highest quant. The results are in percentages, standard errors are in parentheses and the T-tests are two-tailed. All results are statistically significant at the 1% level.
Source: Thomson Financial/CDA-Spectrum

Panel C of Table 22 shows that the average herding in crisis periods is significantly higher for both the lowest- and the highest-beta quants compared to non-crisis periods; however, this higher herding during crisis periods seems to be driven by a higher demand (aversion) for (to) high- (low-) beta stocks. We further explore whether this pattern is systemic during all the crisis periods individually. Our findings in Panel D of Table 22 show that overall average herding in the lowest-beta stocks is largely characterized by buy-herding during the global credit crisis and sell-herding during the dotcom crisis; however, overall herding in the highest-beta stocks is mainly characterized by both buy- and sell-herding during the dotcom crisis.

4.5. Conclusion

Using quarterly holdings of US equity MFs, we investigate the herding dynamics in the long-term trading behavior of US equity MFs over the period 1980 to 2009. Consistent with the mainstream literature, we also use the LSV herding measure to calculate US equity MFs' herding and observe increased herding in their long-term trading behavior. We focus on funds' styles, market volatility, the increased participation of MFs in the financial markets and MFs' size/capitalization as possible determinants of this increased herding in their trading behavior. Our findings show that herding varies significantly across different styles of MFs. Unclassified MFs appear to herd most; however, being dominant in terms of number and capitalization, growth MFs are found to explain most of the overall increased herding in the long-term trading behavior of the MF industry. We also observe slight variations in herding behavior across different deciles of funds' capitalizations (size-deciles), where large MFs appear to herd slightly less than small MFs. We argue that small MFs mimic the trading strategies of large MFs and thus experience higher levels of herding compared to large MFs.

We find that US equity MFs have risk and liquidity preferences in their herding behavior; for instance, they show a significantly higher demand for low-beta compared with high-beta stocks as well as small-sized compared with large-sized stocks. This result answers one of our hypotheses that in the long term, US equity mutual funds limit themselves to certain stock characteristics. The higher demand for smaller-sized stocks confirms the presence of the small-firm-effect anomaly.

Market volatility is found to be one of the important drivers of increased long-term herding in MFs' trading behavior; bear market conditions especially appear to experience much higher herding, about two percent, compared with bullish environments. We observe significantly higher herding levels during crisis periods, which is consistent with the findings of patterson et al. (2006) and inconsistent with the results of Chao et al. (1999).

Chapter 5: Conclusions, Limitations and Recommendation

5.1. Conclusions

We add to the heated debate on trading behavior of institutional investors by investigating empirically their portfolio choice using the portfolio allocation of Dutch PFs and US MFs. Larger part of this study provides empirical evidence on the asset allocation behavior of Dutch PFs across multiple asset classes. The study also provides empirical results of how individual characteristics, such as size, age and cover ratio, of institutional investors drive their long-term asset allocation decisions. Our results show that home bias in the asset allocation decisions of Dutch PFs is diminishing over time and its determinants are – but not limited to the economies of scale, experience, funding status and pension plan.

Chapter 2 of this thesis concludes that, on average, asset allocation decisions across markets are not affected by the PF size; nevertheless, it is relevant from the perspective of the asset allocation of different asset categories across the markets. Economies of scale are demonstrated to provide large PFs with the opportunity to increase their international trade by reducing their domestic bias but only in fixed income. Experience is found to be crucial in international portfolio diversification, wherein we observe a significantly increasing international portfolio diversification for experienced Dutch PFs at a general level vis-à-vis across asset classes; however, this decrease in domestic assets allocation is more pronounced in fixed-income financial instruments. We attribute this activity in experienced PFs to result from experience-related effects and an increasing risk-averseness due to maturity. Our results are consistent with those of Noora and Puttonen (2006) in the sense that maturity affects the asset allocation decisions of Dutch institutional investors.

In contrast to industry PFs, company PFs are significantly more exposed to home bias. We offer the explanation therein that economies of scale allow industry PFs to reduce home bias through experience-based superior portfolio diversification but only in fixed-income assets because their greater experience also indicates an increased maturity, which is accompanied by an increased risk aversion. The introduction of the euro as a common currency (1999) significantly reduces domestic bias; home bias in Dutch PFs' asset allocations decreases by 14%. Our results are consistent with the theory that exchange-rate stability positively affects international trade under the assumption that investors are risk-averse. We find that the dot-com financial crisis has significantly and negatively influenced the trading behaviors of Dutch PFs. This effect is adverse and less strong on domestic equities while positive and more robust on foreign fixed-income securities. We explain these phenomena by an apparent flight to capital in Dutch PFs' investment behavior during the dot-com financial crisis. The cover ratio is found to be a driving force in the asset allocation decisions of Dutch PFs across markets, but only in the riskier assets of lower-sized funds.

Chapter 3 of this thesis focuses on the investment behavior of Dutch institutional investors and provides evidence of high trading activity, feedback strategies and herding behavior in the trading patterns of Dutch PFs. We disproved the theory that all PFs are passive traders by finding that Dutch PFs display a monthly turnover rate of approximately 8.5%. We attribute these findings to a security's individual characteristics, such as liquidity and riskiness. The estimated values of regressions for the turnover measures of Grinblatts et al. (1995) and Ferson et al. (2002) show that turnover is explained in part by a PF's size and contemporaneous returns on equities. We found strong evidence for contrarian trading by Dutch PFs on an aggregate basis; however, it varies considerably across asset classes. Furthermore, we found that lag institutional demand for a security drive momentum investment in riskier assets and contrarian investment in less risky assets. A security's contemporaneous and lagged performance drive contrarian investments across asset classes.

In line with many earlier studies, we also applied Lakonishok, Shleifer and Vishny's (1992) measure to compute the average herding among Dutch PFs. Our results show robust evidence for herding among Dutch PFs, with an average herding of approximately 8.14%, and its presence becomes more obvious as a security's monthly trade increases above more than two active traders. Possible explanations for this trend include outsourcing of portfolio management and small PFs' imitation of large PFs' asset allocation strategies. We also observed herding asymmetry in the buying and selling of securities by Dutch PFs. Across asset classes, we found a higher degree of herding in less risky assets, and we suggest assets' liquidity as the explanation for lower herding in these assets.

Our results indicate that the recent financial turmoil has significantly affected the trading behavior of Dutch PFs. We observed higher turnover as well as increased herding during the crisis. Average herding was higher during the financial crisis but was largely driven by higher sell herding. A higher likelihood of performance based feedback trading was also observed during the crisis.

Chapter 4 of this thesis uses quarterly holdings of US equity MFs to analyse the herding dynamics in their long-term trading behavior over the years 1980 to 2009. Following the main stream literature, we also use LSV herding measure to quantify US equity MFs' herding and observe a increasing herding in their long-term trading behavior. We focus on funds' style, market volatility, increasing participation of the MFs in the financial markets and MFs' capitalization as the possible determinants of this increasing herding in their trading behavior. Our findings show that herding varies significantly across different styles of the MFs. Unclassified MFs appear to herd most; however, being dominant in terms of number and capitalization, growth MFs are found to be effective and explain most of the overall increasing herding in long-term trading behavior of the MFs industry. We also observe slight variations in herding behavior across different deciles of funds' capitalization (size deciles) where large MFs appear to herd slightly less than the small MFs. We argue that small MFs mimic the trading strategies of the large MFs and thus experience higher levels of herding compared to large MFs.

We find that US equity MFs have risk and liquidity preferences in their herding behavior, for instance they show a significantly higher demand for low-beta compared to high beta stocks as well as small sized compared to large sized stocks. This answers one of our hypothesis that in the long-run US equity mutual funds limit themselves to certain stock characteristics. The higher demand for small sized stocks confirms the presence of small firm effect anomaly.

Market volatility is found to be one of the important drivers of long term increasing herding in the MFs trading behavior; especially, bear market conditions are appeared to experience much higher herding, about two percent, compared to bullish environment. We observe significantly higher herding levels during the crisis episodes which is consistent with the findings of Patterson et al. (2006) and inconsistent with results of Chao et al. (1999.

5.2. Limitations

We follow different theories to construct the hypothesis and models and use the available data to develop inferences about these hypotheses. In order to investigate home bias in the Netherlands in Chapter 2, the data used is on annual frequency while the total portfolio holdings are limited to equities and bonds only. One of the major limitations of the home bias research, discussed in

Chapter 2, is low the frequency of the data. Since true effect can be digested by the longer time span and year end reporting may express little about home bias and its determinants.

While investigating trading activity and feedback trading in Dutch PFs in Chapter 3, we remained restricted to explore the existence of feedback trading and herding and determinants of these feedback strategies. Furthermore, we use rather simple models to explore feedback trading and its determinants in Dutch PFs' trading behavior.

Finally, investigating US mutual funds in Chapter 4, we use decile analysis approach rather than doing regression analysis. This can be objectionable but averaging too many factors could have already made our results biased. The main limitation of Chapter 4 is its focus on first stream of literature (i.e. track and measure the presence of herding) which we extensively explored, while the impact of herding – second strand of literature, has been left for the future research.

5.3. Recommendations for Future Research

This research can have significant insights for both academics and professional. We suggest the following lines of research for the future researchers that are able to use the data from DNB.

After introduction of the euro, the euro zone can be considered as home for a euro zone investor compared to rest of the world. With this view the existing research can be extended to explore if the individual country bias has upgraded to 'euro bias'. A set of determinants of 'euro bias' can be the next direction to explore. With a high frequency data, available at DNB, academics and professionals can design an optimal portfolio for the Dutch PFs aligned to their risk preferences. Departure from PPP has been documented as one of the reason of home bias. This can be extended to a new investigation in which International Fisher Effect can be explored as a reason to home bias. One can also focus on home bias as an outcome of the comparative advantage.

Using monthly data of Dutch PFs, we focus on feedback trading strategies and find that herding exists in the trading behavior of the Dutch PFs. Using the same data one can further extend to see if these higher levels of herding also affect the security prices. A more refined data can also help researchers to explore if transaction costs can explain herding? Herding can be event specific (i.e. crisis episodes, earnings announcements, stock splits and reverse splits, mergers and acquisitions) or sector specific for instance in some industries information is very hard to access compared to others or in some industries returns are higher.

We explore existence of herding in US mutual funds. A possible extension of this research is to explore if the herding is event specific phenomenon. Future research can track the situations and factors when herding affects the security prices and drags them towards (away from) their fundamental values.

Summaries

Summary (English)

This study provides an empirical analysis of the investment behavior of institutional investors in two countries. We examine the portfolio choice anomalies and trading strategies of two types of institutional investors, Dutch PFs and US mutual funds (MFs), and present some explanation for the unexpected behavior in their trading. Particularly we focus on the determinants of home bias, feedback trading and herding in the investment behavior of these institutional investors. Given the importance of institutional investment behavior to government, policymakers, investors, economists, academics and practitioners, we explore the potential explanations for these determinants, concentrating on investors' characteristics, properties of the asset classes, market conditions and investors' trading strategies across markets.

Chapter 2 provides an empirical analysis of the asset allocation behavior of Dutch PFs across multiple asset classes and markets. We also analyze how individual PF's characteristics – such as size, age and cover ratio – drive their long-term asset allocation decisions. We find that Dutch PFs' domestic share in portfolio allocation ('home bias') diminishes over time, and that fund characteristics, such as economies of scale, experience, funding status and pension plan (DB or DC), significantly affect their asset allocation across multiple asset classes and markets.Overall, the size of a PF does not influence its asset allocation decisions across markets; however, it is relevant for the asset allocation of different asset categories across the markets. Economies of scale seem to provide large PFs with the opportunity to increase their international holdings by reducing their domestic bias but only in fixed income. Experience is found to be important in international portfolio diversification, as we observe a significantly increasing international portfolio diversification for experienced Dutch PFs across all asset classes; this decrease in domestic assets allocation is more pronounced in fixed-income financial instruments. We attribute the activity of experienced PFs to result from experience-related effects and an increasing risk-averseness for older PFs. Our results are consistent with for instance those of Alestalo and Puttonen (2007) in the sense that the PF age affects asset allocation decisions. Our

results endorse the theory that exchange-rate stability positively affects international portfolio holdings assuming investors are risk-averse.

Chapter 3 examines the investment behavior of institutional investors and provides evidence of high trading activity, feedback strategies and herding behavior in the trading patterns of Dutch PFs. We disprove the theory that all PFs are passive traders by finding that Dutch PFs display a monthly turnover rate of approximately 8.5%. We attribute these findings to a security's individual characteristics, such as liquidity and riskiness. The estimated values of regressions for the turnover measures of Grinblatts et al. (1995) and Ferson et al. (2002) show that turnover is explained in part by a PF's size and contemporaneous returns on equities. We find strong evidence for contrarian trading by Dutch PFs on an aggregate basis; however, it varies considerably across asset classes. Furthermore, we find that lagged institutional demand for a security drives momentum investment in riskier assets and contrarian investment in less risky assets. A security's contemporaneous and lagged performance drives contrarian investments across asset classes.

In line with many earlier studies, we have also applied Lakonishok, Shleifer and Vishny's (1992) measure to compute the average herding among Dutch PFs. Our results show robust evidence for herding among Dutch PFs, with an average herding of approximately 8.14%, and its presence becomes more obvious as a security's monthly trade increases more than two active traders. Possible explanations for this trend include outsourcing of portfolio management and small PFs imitation of large PFs asset allocation strategies. We also observe herding asymmetry in the buying and selling of securities by Dutch PFs. Across asset classes, we find a higher degree of herding in less risky assets, and we suggest assets liquidity as the explanation for lower herding in these assets. Our results indicate that the recent financial turmoil has significantly affected the trading behavior of Dutch PFs. We observe higher turnover as well as increased herding during the crisis. Average herding is found to be higher during the financial crisis but is largely driven by higher sell herding. A higher likelihood of performance based feedback trading is also observed during the crisis.

Chapter 4 uses quarterly holdings of US equity MFs to investigate the herding dynamics in their long-term trading behavior over the period 1980 to 2009. Consistent with the mainstream literature, LSV herding measure has been used to calculate US equity MFs herding and observe increased herding in their long-term trading behavior. We focus on funds styles, market volatility, the increased participation of MFs in the financial markets and MFs size/capitalization as possible determinants of this increased herding in their trading behavior. Our findings show that herding varies significantly across different styles of MFs. Unclassified MFs appear to herd most; however, being dominant in terms of number and capitalization, growth MFs are found to explain most of the overall increased herding in the long-term trading behavior of the MF industry. We also observe slight variations in herding behavior across different deciles of funds capitalizations (size-deciles), where large MFs appear to herd slightly less than small MFs. We argue that small MFs mimic the trading strategies of large MFs and thus experience higher levels of herding compared to large MFs. We find that US equity MFs have risk and liquidity preferences in their herding behavior; for instance, they show a significantly higher demand for low-beta compared with high-beta stocks as well as small-sized compared with large-sized stocks. This result answers one of our hypotheses that “in the long term, US equity mutual funds limit themselves to certain stock characteristics”. The higher demand for smaller-sized stocks confirms the presence of the small-firm-effect anomaly. Market volatility is found to be one of the important drivers of increased long-term herding in MFs trading behavior; bear market conditions especially appear to experience much higher herding, about two percent, compared with bullish environments. We observe significantly higher herding levels during crisis periods, which is consistent with the findings of Sharma et al. (2004) and inconsistent with the results of Chao et al. (1999).

Samenvatting (Dutch)

Deze studie analyseerthet investeringsgedragvan de institutionele beleggers intwee landenen voor twee typen institutionele beleggers. We onderzoeken deanomalieën in portefeuillekeuze enhandelsstrategieënvan twee soorteninstitutionele beleggers, Nederlandse pensioenfondsen(PFn) en de Amerikaanse beleggingsfondsen (MFs), enpresenteren een aantalverklaring voor hetonverwachtegedrag inhun handel. We richten ons vooral opde determinanten van“home bias”, feedback handel enlemming-gedrag inhet investeringsgedrag vandeze institutionele beleggers.[44] Wij concentreren ons opbeleggerskenmerken,eigenschappen van deactivaklassen, marktomstandigheden ende beleggers handelsstrategieën inmarkten voor mogelijke verklaringen voordeze determinantengezien het belang vaninstitutioneel beleggingsgedragvoor beleidsmakers, investeerders en academici.

Hoofdstuk 2 vandit proefschriftbevat een empirische analyse van deactiva allocatie gedrag van Nederlandse pensioenfondsenover meer derebeleggingscategorieën enmarkten.We analyseren ook hoede individuelePF-kenmerken-zoals omvang, leeftijd en dekkingsgraad-de lange termijnactiva allocatiebeïnvloeden. We vinden dathet binnenlandse aandeelin de portefeuille vande toewijzingvan Nederlandse PF ('homebias') vermindertna verloop van tijd, endat fondskenmerken, zoalsschaalvoordelen, ervaring, de financieringsstatus enpensioenregeling(‘defined benefit’of ‘definedcontribution’), significant zijn voor hunactiva allocatieover meerdereactivaklassen enmarkten.Over het geheel genomenheeft degrootte van eenPFgeen invloed opdeactiva-allocatiebeslissingenover markten, maar het iswel van belang voor deactiva allocatievan de verschillendebeleggingscategorieënover demarkten.SchaalvoordelenlijkengrotePFdemogelijkheid te geven ominternationaal teinvesteren , maar alleen in vastrentende waarden. Ervaring blijkt belangrijk te zijnvoor de internationalediversificatie van de portefeuille, aangezien we eensterkgroeiende internationalediversificatie van de portefeuillevoor deervaren NederlandsePFin alleactivaklassen zien. Deze trend is meer uitgesprokenvoor vastrentendefinanciële instrumenten. Wesuggereren dat deactiviteitvan ervarenPFnvoortvloeit uitervaring-gerelateerde effecten en eentoenemend risico-afkeer van ouderePFn. Onzeresultaten zijn consistent metbijvoorbeelddie van Alestalo en Puttonen (2007) in die zin datde PF-leeftijd activa-allocatiebeslissingenbeïnvloedt.

[44]“Home bias” is het concept dat een belegger te veel in het thuisland belegt (tov een (optimaal) gespreide portefeuille).

Onzeresultaten onderschrijvende theorie datwisselkoersstabiliteit internationale portefeuille-allocatie positiefbeïnvloed.

Hoofdstuk 3 vandit proefschriftonderzoekthet investeringsgedrag vaninstitutionele beleggers enlaat hogehandelsactiviteit, feedback strategieën enkuddegedraginde handelspatronen van deNederlandsePF zien. We weerleggende theorie datalle PF passievehandelarenzijn aangezien NederlandsePFeen maandelijksongeveeracht enhalf procent van hun portefeuille verhandelen.Weschrijven dezebevindingentoe aan risicokenmerken, zoalsmarktliquiditeit enrisicogehalte. De regressie coëfficiënten voor deomzetmaatstaven à la Grinblattset al.(1995) enFersonetal.(2002)laten zien dat de omzetdeels wordt verklaarddoor de omvang van eenPFen gelijktijdigerendementen opaandelen. We vindensterk bewijsvoorcontraire handelvan NederlandsePF, hoewel de resultaten aanzienlijk verschillen per beleggingscategorieën.

In lijnmet veeleerderestudies hebben weook de Lakonishok, Shleiferen Vishny's (1992) maatstaven toegepast om degemiddeldelemming-gedrag (“herding”) onder de NederlandsePFberekenen.Onzeresultaten tonen overtuigend bewijsvoor dergelijk gedrag van Nederlandse PF zien, met een gemiddelde herdingvan ongeveer 8,14%. De aanwezigheid ervanwordt duidelijkerbij meer dan tweeactieve handelaren. Mogelijke verklaringenvoor deze trendzijn hetuitbestedenvan portfolio managementen het navolgen van de grotePFn door kleine PFn.We hebben ookasymmetrische herdinggezieninde aankoop en verkoopvan effecten door Nederlandse PF. In alle activaklassen,vonden we eenhogere mate vanherdingin minderrisicovolle activa, enwe suggereerden activa 's liquiditeitswaardeals deverklaring voor het lagereniveau van herdingindeze activa. Onzeresultaten geven aan datde recente financiële onrusthet handelsgedrag van Nederlandse PF aanzienlijk heeft beïnvloed: We zageneen hogere omzeten een toename vanherdingtijdens de crisis.Gemiddeldeherdingwas hogertijdens de financiëlecrisis, maarwerd voornamelijk veroorzaakt doorhogereverkoopherding.

Hoofdstuk 4 maakt gebruik vankwartaal-gegevensvan Amerikaanse aandelen beleggingsfondsen (Mutual funds, oftewel MFs) om herding-dynamiekte onderzoekenin het lange-termijn handel gedrag van deze MFsoverde periode 1980 tot 2009. In overeenstemming metde mainstreamliteratuur, gebruiken wij de LSV herding maatstaven voor Amerikaanse aandelen MFs. Wij richten ons opfondsstijlen, marktvolatiliteit, degrotere deelnamevan MFs op de financiële marktenen MFs ovang en kapitalisatieals mogelijke determinanten vanhet verhoogdekuddegedragin hun handelsgedrag. Onze bevindingentonen aan dathet herdensterkvarieert tussen deverschillende stijlen vanMFs. ‘MFs zonder classificatie’ lijkenhet meeste te herden maar, aangezien ze dominant inaantalen kapitalisatie zijn, 'groei MFs'hebben het grootste aandeel in de bepaling van het geaggregeerde langetermijn handelsgedrag van deMF-industrie. We zien ookkleine variaties inkuddegedragvoor de verschillendedecielenvan fondskapitalisaties (omvang-decielen), waar grotefondsen iets minderkuddegedrag lijken te laten zien dan kleine fondsen. We argumenteren datkleinefondsen dehandelsstrategieënvan grotefondsen na bootsenen zoeen hoger niveau van kuddegedrag laten zien. We vindendat de Amerikaanse aandelen MFn liquiditeitsrisico-voorkeurenin hunkuddegedraghebben; zo laten zijeen significant hogerevraag naar laagbèta aandelen in vergelijking methoge bètaaandelenzien. Ook hebben zij een voorkeur voor kleineboven grote aandelen. Dit resultaatis relevant voor een van onzehypothesen, namelijk dat op de lange termijn, Amerikaanse aandelenbeleggingsfondsenzich beperken toteen beperktaantal aandelen. De hogerevraag naarkleinereaandelen bevestigt deaanwezigheid van het zogenoemde 'small stock effect'.Marktvolatiliteit blijkt een van debelangrijke drijfverente zijn van verhoogdelange termijnkuddegedragin het handelsgedrag van MFn; met name in een neergaande marktlijken kuddegedrag veel hoger,ongeveer twee procent, in vergelijking met opgaande markt.We zien significant meer kuddegedrag tijdenscrisisperiodes, dit in overeenstemming met de bevindingen van Sharma et al.. (2004) enin strijd met deresultaten van Chaoet al.. (1999).

Appendices

Appendix A: The Adjustment Factor

The following numerical example shows the necessity and calculation of the adjustment factor. We use the following assumptions: the expected fraction of buyers (P_t) in period t is 0.55 (i.e., 55% of the transactions are buy transactions), the number of PFs active in stock X during period t is five, and two PFs are buying stock X. When the $HM_{i,t}$ is calculated without the adjustment factor ($|B_{i,t} / (B_{i,t} + S_{i,t}) - P_t|$), the result would be $|2/(2+3) - 0.55| = 0.15$, but this is not true herding because the real fraction of buyers can never equal 0.55 if five PFs are active. Therefore, we must adjust the $HM_{i,t}$ outcome for stock X in period t with the expected outcome of $|B_{i,t} / (B_{i,t} + S_{i,t}) - P_t|$ when five PFs are active in stock X.

The expected outcome of $|B_{i,t} / (B_{i,t} + S_{i,t}) - P_t|$ is the sum of all possible outcomes, multiplied by their probability of occurring. The probability of occurring can be calculated as follows:

$$P(X = x) = \binom{n}{x} p_t^{\,x} * (1 - p_t)^{n-x}$$

where n is the number of active PFs, x is the number of buyers, and pt is the expected fraction of buyers. The following presents the calculations for the expected outcome of $|B_{i,t} / (B_{i,t} + S_{i,t}) - P_t|$.

P(X=x)	$B_{i,t} = x$	$B_{i,t} / (B_{i,t} + S_{i,t})$	P_t	$\lvert B_{i,t} / (B_{i,t} + S_{i,t}) - P_t \rvert$
0.01845	0	0	0.55	0.01015
0.11277	1	0.2	0.55	0.03947
0.27565	2	0.4	0.55	0.04135
0.33691	3	0.6	0.55	0.01685
0.20589	4	0.8	0.55	0.05147
0.05033	5	0.1	0.55	0.02265
		$E\ \lvert B_{i,t} / (B_{i,t} + S_{i,t}) - P_t \rvert$		0.18193

The $HM_{i,t}$ including the adjustment factor is $|2/(2+3) - 0.55| - 0.18193 = -0.03193$. This is the fraction of PFs that traded on one side of the market above (or below in this case because of the negative sign) expectations based on the expected fraction of buyers in that period. Without the adjustment factor, we would have overestimated the level of herd behavior.

Appendices

Appendix B: Further Statistics

The distribution of PF types with respect to benefit schemes they are offering.

	Benefit Type			
PF Type	Hybrid	DB	DC	Total
Industry	9	1347	100	1456
Company	291	9754	887	10932
Others	0	15	73	88

Correlation matrix for the variables that were analyzed in our regressions

	Size	Dependency ratio	Cover ratio	Technical provisions	PFage
Size	1				
Dependency ratio	-0.0027	1			
Cover ratio	-0.0034	0.8121	1		
Technical provisions	0.9853	-0.0028	-0.0037	1	
PF age	0.0631	-0.0364	-0.0440	0.0581	1
Participants' ave. age	0.0112	-0.0271	-0.0224	0.0112	0.0103

Appendices

The distribution of PFs' sizes and the benefit schemes that they are offering

	Benefit Type			
PF Size	Hybrid	DB	DC	Total
Small	283	4168	762	5213
Medium	27	6648	380	7055
Large	0	659	8	667
Total	310	11,475	1,150	12,935

The distribution of PFs' size in relation to their types

	Type of the Pension Fund			
PF Size	Industry PFs	Company PFs	Other PFs	Total
Small	151	4594	70	4815
Medium	970	6027	25	7022
Large	351	312	0	663
Total	1372	10933	95	12500

Appendix C: Correlation Matrix

Correlation between different variables					
	Quarterly herding	No. of Funds	quarterly assets	No. of Securities	Quarterly volatility
Quarterly Herding	1				
No. of funds	0.5067	1			
quarterly assets	0.1986	0.4408	1		
No. of securities	0.4387	0.5917	0.4763	1	
Volatility	-0.056	0.266	0.3547	0.2303	1

Notes: 1 presents the correlation between different potential factors that may affect the quarterly herding. Here Quarterly herding is the average LSV quarterly herding, No. of funds are the MFs that involved in trading during quarter, No. of securities represents the securities traded during a certain quarter and volatility is CBOX quarter-VIX.

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Biography

Ghulame Rubbaniy was born on June 5, 1975 in Faisalabad, Pakistan. He studied his undergraduate degree in Mathematics at the University of Punjab. After completing his M.Sc. in Statistics from University of Agriculture Faisalabad, he has been teaching business mathematics and statistics to undergraduates at various educational institutions in Pakistan during the years 2000-2006. In 2006, he got a scholarship from Higher Education Commission of Pakistan for MS leading to PhD and earned his M.Sc. degree from Tilburg University in 2007 with a major in Finance and Economics.

In 2007, Rubbaniy started his PhD at Nijmegen School of Management, Radboud University Nijmegen and his research proposal was accepted by De Nederlandsche Bank (Dutch Central Bank) as a part of his PhD project. He joined supervisory division of De Nederlandsche Bank (DNB) as part time researcher and successfully participated in two projects of DNB. He moved to Erasmus University Rotterdam in 2008 and supervised various master research theses at Erasmus School of Economics (ESE). His research interests include commodity and alternative investments, capital structure, portfolio optimization, pension funds and mutual funds. He has won a few travel grants and enjoys a good experience of research presentations at major finance conferences including, Australian Banking and Finance conferences Australia, Pennsylvanian Economic Association the US, NetSpar the Netherlands, Multinational Finance Association Italy, Portuguese Finance Association Portugal, Brunel Business School the UK and ERIM. His work is forthcoming in ***The European Journal of Finance*** and also holds a revise-and-resubmission in ***De Economist***.

Besides his academic activities, Rubbaniy has been an active member of ESE sports dream-team and also been a volunteer for *Kinderboekenweekfeest*. Currently, Rubbaniy holds a position as an Assistant Professor of Finance and Director Graduate Program at UCP Business School, University of Central Punjab.

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INVESTMENT BEHAVIOR OF INSTITUTIONAL INVESTORS

This study examines the portfolio choice anomalies and trading strategies of two types of institutional investors, Dutch pension funds (PFs) and US mutual funds (MFs), and presents some explanation for the unexpected behavior in their trading. Particularly we focus on the determinants of home bias, feedback trading and herding in the investment behavior of these institutional investors. We find that Dutch PFs' domestic share in portfolio allocation ('home bias') diminishes over time, and that fund characteristics, such as economies of scale, experience, funding status and pension plan (DB or DC), significantly affect their asset allocation across multiple asset classes and markets. We disprove the theory that all PFs are passive traders by finding that Dutch PFs display a monthly turnover rate of approximately 8.5%. We find strong evidence for contrarian trading by Dutch PFs on an aggregate basis; however, it varies considerably across asset classes. Furthermore, we find that lagged institutional demand for a security drives momentum investment in riskier assets and contrarian investment in less risky assets. A security's contemporaneous and lagged performance drives contrarian investments across asset classes. Using quarterly holdings of US equity MFs we investigate the herding dynamics in their long-term trading behavior and find that funds styles, market volatility, the increased participation of MFs in the financial markets and MFs size/capitalization are important determinants of herding dynamics in their trading behavior. The results endorse one of our hypotheses that "in the long term, US equity mutual funds limit themselves to certain stock characteristics".

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