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Institutional Herding in Bond Markets

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Institutional Herding in Bond Markets

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Abstract:

Recent research has shown that institutional herding is a relevant phenomenon in stock markets. Do institutional investors also follow each other in bond markets? This paper focuses on the German bond market and uses data from 57 German mutual funds that invest mainly in DM-denominated bonds, which represents 71% of the total market volume. Due to the variety and large number of bonds that exist, we do not expect mutual funds to herd with regard to separate bonds. We believe instead that bonds with the same characteristics such as interest rate, maturity, collateral, or issuer are considered to be equivalent by institutional investors. Consequently, we construct "bond groups" consisting of similar bonds and analyze herding at a "bond group" level. Our results indicate that there is strong evidence of herding, albeit it is weaker than in stock markets. Further analysis suggests that mutual funds do not place an equal weight on different bond characteristics. Nominal interest rates appear to be most important in the bond selection process.

JEL Classification: D7, G21

Key words: Mutual Funds, Herding, Imitation, Coordination, Behavioral Finance

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Recent research has shown that institutional herding is a relevant phenomenon in stock markets. Do institutional investors also follow each other in bond markets? This paper focuses on the German bond market and uses data from 57 German mutual funds that invest mainly in DM-denominated bonds, which represents 71% of the total market volume. Due to the variety and large number of bonds that exist, we do not expect mutual funds to herd with regard to separate bonds. We believe instead that bonds with the same characteristics such as interest rate, maturity, collateral, or issuer are considered to be equivalent by institutional investors. Consequently, we construct "bond groups" consisting of similar bonds and analyze herding at a "bond group" level. Our results indicate that there is strong evidence of herding, albeit it is weaker than in stock markets. Further analysis suggests that mutual funds do not place an equal weight on different bond characteristics. Nominal interest rates appear to be most important in the bond selection process.

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1. INTRODUCTION

One of the most natural human traits is our need to imitate. As children we have idols that we want to be like when we grow up, in our sports clubs we use the same equipment that famous players use, and we go to restaurants that friends have recommended. Imitation is a necessary part of the evolutionary process, it prevents us from making the same mistakes as others and allows us to learn from each other.

The phenomenon of imitation and herding is not only important to social aspects of life, however, but it also pertains to economic situations. Financial markets are inherently susceptible to herding due to the large volume of relevant information and the complex task of security analysis¹. Much research has focused on the behavior of institutional investors. This type of investors has become more and more important over the years and their investment decisions potentially have an impact on security prices, as institutional investors trade large volumes at once². It is straightforward that herding magnifies trading volumes in a subset of securities and, therefore, increases potential price volatility.

Recent research on institutional herding in stock markets has shown that there is indeed a tendency of investors to be on the same side of the market at the same time³. Apparently, institutional investors are not as rational and sophisticated as we expect them to be, relying much on interpersonal communication, fads, and rumors. Herding is also found to be a driving force behind stock price movements.

This study aims at searching for evidence of institutional herding in the German bond market. The variety and large number of bonds require a different methodological approach than in the stock market studies. Institutional investors select bonds with regard to important characteristics such as interest rate, maturity, collateral, duration, issuer, and ratings. We believe that similar bonds are considered to be equivalent by investors and, hence, we construct "bond groups" that comprise bonds with the same salient features. Herding is then analyzed at a "bond group" level. The formulation of meaningful criteria for the aggregation process clearly constitutes a critical step in our study. The results suggest that herding is an observable phenomenon in bond markets, albeit it is weaker than in stock markets.

This paper is structured as follows. Section 2 reviews theories and models of herding, while in section 3 we discuss empirical studies of herding in stock markets. Section 4 describes the design of the bond market study, section 5 presents our results, and section 6 concludes.

2. THEORIES AND MODELS OF HERDING

2.1 DEFINITION OF HERDING

Academics have used various definitions of herding with regard to their respective research objectives. Herding has been defined as "a group of investors trading in the same direction over a period of time" (Nofsinger and Sias (1998)), "behavior patterns that are correlated across individuals" (Devenow and Welch (1996)), and is said to occur when "individuals alter their private beliefs to correspond more closely with the publicly expressed opinions of others" (Cote and Sanders (1997)). Clearly, herding implies that individuals behave alike. However, this notion of similarity alone is insufficient. Correlated behavior might arise simply

¹ Keynes (1936) early used the famous metaphor of the beauty contest to describe the behavior of investors.

² The price impact of institutional trading has been studied by Kraus and Stoll (1972b), Harris and Gurel (1986), Holthausen et al. (1987), Chan and Lakonishok (1993, 1995), Teh and de Bondt (1987), Christie and Huang (1995), and Nofsinger and Sias (1998).

³ See Kraus and Stoll (1972a), Lakonishok et al. (1992), Grinblatt et al. (1995), Wylie (1998), Oehler (1998), and Wermers (1999).

by chance or because individuals have access to the same sources of information or interpret information similarly. Hence, a further intentional element has to be added that can best be circumscribed as social pressure, social learning, imitation, or conformity. The latter has been defined by Aronson (1992) as "a change in a person's behavior or opinions as a result of real or imagined pressure from a person or a group". Due to this psychological element herding then leads to systematic sub-optimal decision-making relative to the best aggregated choice. Note that herding does not automatically imply irrational behavior. There are many circumstances in which individuals alter their behavior in a rational way as a response to perceived social pressure.

2.2 PRINCIPAL-AGENT MODELS

The key characteristic of this type of models is that relative performance evaluation and reputational concerns of managers or analysts cause principal-agent problems⁴. In such a setting, agents will herd and mimic the investment decisions or earnings forecasts of other agents in order to convey to their principals that they possess superior skills⁵.

The models developed by Scharfstein and Stein (1990), Trueman (1994), and Graham (1999) assume that there are *different type of agents*. Specifically, there are two agents that sequentially have to make an investment decision and both agents have access to privately observed signals about the investment payoff. Smart agents receive informative private signals, while dumb agents receive purely noisy signals. An agent's compensation depends on the principal's assessment of his abilities. The critical assumption is that the informative signals of smart agents are correlated, because they are all "observing a piece of the same 'truth'" (Scharfstein and Stein (1990)), while the noisy signals of dumb agents are uncorrelated. Hence, if an agent mimics the decisions of others, principals will believe that he has received a correlated signal and is thus likely to be smart. In addition to this "look-smart"-effect, there is also a "share-the-blame"-effect of herding. If the decision turns out to be a mistake, the agent can share the blame with many others. With correlated informative signals there is always an incentive for an agent to herd.

Zwiebel (1995) presents a model in which agents have *different action spaces*. There are many agents that can undertake an old action (e.g. the industry standard), while a few agents can additionally choose to adopt a new action (e.g. a new technology) that stochastically dominates the old one. The true values of both actions are unknown, however. Nevertheless, the principals have a relatively accurate benchmark for the old action, since they can infer its true value due to the large number of agents that undertake it. Conversely, they only have a noisy estimate of the new action's true value. Under such conditions, an agent with average skills who can choose between both actions will prefer the old action for which a benchmark exists.

Maug and Naik (1995) and Palley (1995) demonstrate that an *explicit relative performance clause* can induce herding. In the model of Maug and Naik (1995), there is one agent A who trades on his own account and another agent B who manages a portfolio for a principal. The compensation of agent B is an increasing function of the profits he earns and a decreasing function of agent A's profits. The formal analysis of the equilibrium shows that under certain

⁴ Morck et al. (1989) found out that that complete management turnovers are associated with poor performance relative to the industry. Palley (1995) and Maug and Naik (1995) suggest that the belief of a manager that his promotion and the renewal of his contract depend on the performance of others suffices to implicitly capture the element of relative performance evaluation.

⁵ Herding among financial analysts has been studied empirically by Stickel (1990, 1992, 1995), Olsen (1996), Cote and Sanders (1999), de Bondt and Forbes (1999), and Welch (1999). Cote and Goodstein (1999) discuss ethical implications of analysts' herding. See also Stickel (1992, 1995).

conditions, agent B will decide to trade in the same asset as agent A. An extension of the analysis suggests that in extreme cases agent B will buy even when his own information is telling him to sell and vice versa. Palley (1995) discusses a model in which both agents face a relative performance clause. This setting leads to a Cournot-Nash equilibrium in which the portfolio allocations of the two agents are interdependent.

2.3 INFORMATION ACQUISITION MODELS

This type of models focus on information acquisition patterns of investors. Herding arises when all investors choose to study the same assets or sources of information or when investors purchase information only if many other investors do.⁶

Short-term trading horizons are the main element of the models by Brennan (1990) and Froot et al. (1992). Short-term investors close their positions before fundamental asset values are known. This leads to positive informational spillovers: the more other investors trade on the same information, the more an investor will earn a profit. The reason is that by the time the investor unwinds his position, he will only gain if the information he traded on is incorporated into the market price. This will only occur, however, if many other investors traded on the same piece of information. Consequently, short-term investors will choose to study sources of information that are also widely studied by other investors.

Hirshleifer et al. (1994) present a model with *different types of investors*. Some investors discover information before others, and these early-informed investors gain by unwinding their positions when their information has been impounded into the market price due to the trades of late-informed investors. However, ex ante the investors do not know whether they are early informed or late informed. The analysis suggests that the expected ex ante utility of an investor is an increasing function of the total number of informed investors. Hence, investors will herd and acquire the same information.

2.4 INFORMATIONAL CASCADE MODELS

The notion of informational cascades suggests that the behavior of other individuals conveys information to an observing individual. At a certain point, this individual will disregard his own information and follow the decisions of others. Subsequent individuals will then find this individual's action to be uninformative, which puts them in the same situation, causing them to ignore their own information and engage in herding as well⁷.

Further analysis suggests that a cascade must eventually occur and that the probability of a cascade is an increasing function of the number of individuals⁸. It can also be shown that cascades tend to be wrong, i.e. individuals reject although the true value of V is high and vice versa⁹. As far as welfare properties, informational cascades can therefore be inefficient in an ex ante welfare sense¹⁰. The reason is that once an informational cascade starts, no more private information is revealed.

⁶ Calvo and Mendoza (1997) formulate a model in which investors choose *not* to acquire information to verify rumors about asset returns. Golec (1997) provides an empirical example of herding on information acquisition.

⁷ The basic model of informational cascades has been developed by Banerjee (1992) and Bikhchandani et al. (1992). Welch (1992) presents a similar model in the IPO market and Neeman and Orosel (1999) study informational cascades in an auction market. See also Smith and Sørensen (1997, 1999).

⁸ See Bikhchandani et al. (1992)

⁹ See Bikhchandani et al. (1992). See also Vives (1996) for a discussion on the self-defeating aspect of social learning.

¹⁰ See Banerjee (1992).

Extensions of informational cascade models discuss the role of fashion leaders (Bikhchandani et al. (1992, 1998)), the fragility of cascades (Bikhchandani et al. (1992)), the relevance of continuous action spaces (Gul and Lundholm (1995), Gale (1996)), the impact of endogenous timing (Gul and Lundholm (1995), Zhang (1997)), the existence of multidimensional uncertainty (Avery and Zemsky (1995)), and the volatility of the environment (Hirshleifer and Welch (1998)).

2.5 BEHAVIORAL MODELS

This type of models is often referred to as models of "irrational" or "near-rational" herding. They use a behavioral approach to analyze issues like investor psychology, interpersonal communication, or contagion of interest that are the sources of irrational decision-making.

There has been some research on the relevance of *interpersonal communication*. Shiller and Pound (1989) undertook questionnaire surveys and found out that investors did not seem to be systematic in their buying decisions and that both institutional and individual investors' initial interest in a stock was stimulated by other investors. Shiller (1990) also used a survey methodology to analyze the behavior of economic actors in speculative environments. His results indicate that people react to each other, relying much more on emotion and intuition than systematic research.

Pingle (1995) conducted an *experiment on imitation* to see when individuals are likely to follow others. The results indicate that imitation is more likely when a decision is made for the first time, a change in the decision-making environment occurs, and when the decision-making environment is competitive or challenging.

Topol (1991) presents a model in which traders that have to set bid/ask prices possess limited information sets. Knowing that other traders have different information, a trader will therefore herd and adjust his prices relative to other traders' prices. Such a behavior is called *mimetic contagion* and allows the trader to implicitly extend his own information set. Further analysis shows that speculative bubbles can be explained by mimetic contagion.

The model by Lux (1995) explicitly incorporates *psychological factors* which influence the behavior of non-sophisticated traders. These traders do not have access to information about fundamental values and, therefore, they have to base their actions on observations of the market. Psychological factors are modeled as follows. Traders can either be optimistic or pessimistic. Suppose that there is a high proportion of optimistic traders. Because traders are non-sophisticated and susceptible to other traders' behavior, it is very likely that the remaining pessimistic traders change their attitudes and become optimistic as well. Herding is therefore characterized as contagion of sentiment.

3. EMPIRICAL STUDIES OF HERDING IN STOCK MARKETS

3.1 SAMPLE CHARACTERISTICS

Table 1 provides an overview of six studies that search for evidence of institutional herding in stock markets. The studies mainly vary in the sample sizes and the type of trading data used. With regard to the latter, only Kraus and Stoll (1972a) use actual trading information. All other studies calculate changes in portfolio holdings to serve as proxies for actual transactions. Consequently, positions that are opened and closed during a reporting period are not included. Furthermore, only herding between two reporting dates can be measured. If funds herd in shorter intervals than the frequency of the trading data, the studies are unable to capture it.

Table 1 – Empirical studies on institutional herding in stock markets

	Kraus and Stoll (1972a)	Lakonishok, Shleifer, and Vishny (1992)	Grinblatt, Titman, and Wermers (1995)	Wylie (1998)	Oehler (1998)	Wermers (1999)
Frequency and type of data	Monthly trading data	Quarterly portfolio holdings	Quarterly portfolio holdings	Semi-annual portfolio holdings	Semi-annual portfolio holdings	Quarterly portfolio holdings
Number and type of institutional investors	229 US banks and investment companies	769 US pension funds	274 US mutual funds	268 UK mutual funds	28 German mutual funds	Virtually every US mutual fund
Time period	1968-1969	1985-1989	1974-1984	1986-1993	1988-1993	1975-1995
Type of herding	Market-wide herding	Excess herding	Excess herding	Excess herding	Excess and market-wide herding	Excess herding
Herding measures used	HV	H	H	H	H, HF, HV	H
Results for excess herding		Weak evidence H = 0.027	Weak evidence H = 0.025	Weak evidence H = 0.026	Weak evidence H = 0.027	Weak evidence H = 0.034
Results for market-wide herding	No evidence				Strong evidence	

3.2 HERDING MEASURES

The studies essentially use three different measures to explore evidence of herding¹¹. One central herding measure has been defined by Lakonishok et al. (1992). It is formally expressed as:

$$H(i) = \left| \frac{B(i)}{B(i) + S(i)} - p(t) \right| - AF(i)$$

For any period t , $B(i)$ is the number of mutual funds that have bought a stock i and $S(i)$ is the number of mutual funds that have sold a stock i . $p(t)$ is the total number of mutual funds buying in period t relative to the total number of mutual funds active in period t . $AF(i)$ is an adjustment factor and accounts for the fact that under the null hypothesis of no herding the first expression can be greater than zero. It therefore represents the expected value of the first expression under the null hypothesis of no herding¹².

A nonzero value for $H(i)$ indicates the degree to which mutual funds herd more in a given stock than the trading behavior over all bonds would suggest. In other words, $H(i)$ only measures excess or stock-picking herding¹³; if the market as a whole was showing a tendency to be on the same side (market-wide herding), it would not be considered to be herding. Such a view seems to be consistent with information-based models of herding which explain herding with regard to individual stocks. Correlated behavior that is induced by noninformational parameters (e.g. a large proportion of buy transactions due to a bullish environment) cannot be classified as herding in these models.

Conversely, principal-agent models and behavioral models suggest that market-wide herding be relevant. Due of reputational concerns, investors might buy just because others are buying as well; psychological factors provide a possible explanation for general market sentiments (optimistic vs. pessimistic) and corresponding behavior. One measure of market-wide herding has been defined by Oehler (1998). *Herding of Fund managers* is expressed as

$$HF(i) = \left| \frac{B(i) - S(i)}{B(i) + S(i)} \right|$$

where $B(i)$ is the number of mutual funds that have bought a stock i and $S(i)$ is the number of mutual funds that have sold a stock i . In the case of no herding $HF(i)$ would be zero, while a value of one indicates that all mutual funds active in a stock i have bought (sold) that stock.

However, even if $HF(i)$ was zero, there might be a price impact, since it is possible that the buyers are making larger trades than the sellers and vice versa. Oehler (1998) therefore defines a second measure to analyze *Herding* corresponding to traded Volume. It is expressed as

$$HV(i) = \left| \frac{BV(i) - SV(i)}{BV(i) + SV(i)} \right|$$

where $BV(i)$ is the volume traded by mutual funds buying a stock i and $SV(i)$ is the volume traded by mutual funds selling a stock i . Again, the value range for HV is $[0,1]$. One limitation to the measures HF and HV is the integer-value procedure which doesn't allow to distinguish between buy-herding and sell-herding.

¹¹ The original notation in the different studies has been modified in order to ease comparability.

¹² Under the null hypothesis of no herding, in any period t the probability of a randomly selected mutual fund being a net buyer is $p(t)$. $B(i)$ follows a binomial distribution with probability $p(t)$ of success, and for a given stock i and n active mutual funds

$$AF(i) = \left(\frac{n}{np(t)} \right) p(t)^{np(t)} (1-p(t))^{n(1-p(t))}$$

¹³ See also Oehler (1998).

A critical assumption of all three herding measures is that the transactions of mutual funds follow a binomial distribution: they can either be a buy or a sell transaction. One corollary is then that short selling must be possible. Take a mutual fund that has an initial holding in stock i of zero. Only if short selling was allowed can this mutual fund be a seller of this stock; otherwise he can only be a buyer and his actions would not be binomially distributed. The short selling assumption is a very strong one, since in reality only few mutual funds can undertake short sales. Wylie (1998) has analyzed the distortion arising from this invalid assumption and found out that herding tends to be overstated. This intuitively makes sense, since the reason why some mutual funds buy a stock might be that their initial holding was zero and that they cannot short sell. The herding measures would then incorrectly interpret this behavior as strong evidence of herding. It is necessary to bear this caveat in mind when analyzing the results of the different studies.

3.3 FINDINGS

As far as excess herding, all studies only find relatively weak evidence of such a behavior. The level of herding as measured by H varies between 0.025 and 0.034. Herding seems to be more pronounced for small stocks, which can be explained by the smaller amount of information available for small stocks¹⁴. Increasing the activity level (minimum number of trades in a stock) yields contradictory results: Grinblatt et al. (1995) and Wylie (1998) find that herding is positively related to the number of mutual funds active, whereas the results in Lakonishok et al. (1992) and Wermers (1999) do not confirm such a relationship.

The results for market-wide herding are ambiguous. Kraus and Stoll (1972a) come to the conclusion that there is no evidence of market-wide herding in their dataset, while Oehler (1998) finds strong evidence of market-wide herding. The discrepancy stems from the benchmark used in the two studies. Oehler (1998) calculates expected values of HF and HV under the null hypothesis of no herding, and the benchmark values are virtually zero. Kraus and Stoll (1972a), however, simulate two datasets based on the frequency distributions of the original dataset. Since the directions and magnitude of the trades in the simulations are determined by chance, HV values for the simulations are then solely due to chance as well. The HV values for the original dataset do not vary significantly from these simulated values, which is why Kraus and Stoll (1972a) conclude that there is no evidence of systematic herding. However, HV values are in fact relatively high (0.255 for large NYSE stocks, 0.640 for other NYSE stocks, and 0.836 for AMEX stocks), which is supportive of market-wide herding. The validity of using simulations as benchmark has therefore to be questioned. Additionally, Oehler (1998) finds that market-wide herding is more likely to occur for small stocks. Neglecting the simulation approach, the results of Kraus and Stoll (1972a) indicate the same phenomenon (HV is higher for AMEX stocks than for large NYSE stocks).

4. DESIGN OF THE BOND MARKET STUDY

4.1 DATA

Our analysis is based on a sample of 57 German mutual funds that specialize in DM-denominated bonds for the three-year period from 1993 to 1995. Each mutual fund reports its portfolio holdings twice a year, with June/December and March/September being the most

¹⁴ See Zeghal (1984) for a discussion about the informational content of small firms' financial statements and Falkenstein (1996) for mutual funds' preferences for certain stock characteristics.

common reporting dates. We obtained portfolio information from the investment companies directly. At the end of 1995, these 57 mutual funds accounted for DM 25 billion, or 71% of the total market volume¹⁵.

Changes in portfolio holdings were calculated and served as proxies for trading volume during a half-year. The main limitation to this procedure is that we are not able to detect herding that occurs in shorter intervals than a half-year. It was not possible to obtain trading data with higher frequency.

Since the mutual funds had different reporting dates, we had to divide our sample into two subsamples. Although most mutual funds had reporting dates in March/September, the largest mutual funds reported their portfolio holdings in June and December.

Our analysis shows that the results are not dependent on when the mutual funds have their reporting dates. The following sections therefore only document our findings for mutual funds that report their portfolio holdings in June/December.

4.2 CATEGORIZATION OF BONDS

Due to the nature of bonds and the large number of different bonds that are traded, we do not expect mutual funds to herd with respect to individual bonds. We believe instead that mutual funds base their trading on important characteristics of bonds, such as interest rate, maturity, issuer, and collateral. Bonds with the same salient features are then considered to be equivalent. Consequently, we aggregate similar bonds and analyze mutual funds' trading of these "bond groups".

With respect to the dataset available, we used the following criteria for the classification of bonds:

- Nominal interest rate

Categories with intervals of 50 basis points were constructed, which resulted in a total of 21 different bond groups. Table 2 shows that the majority of bonds have a nominal interest rate between 5.50% and 7.00%.

- Type of quality

This criteria serves as a proxy for collateral and rating. There are three different characteristics. Bonds can be eligible as collateral for a loan as determined by the Bundesbank, the German central bank. They can also be eligible as a security for a cover fund¹⁶. Finally, bonds can be "gilt-edged". The combination of these three characteristics leads to the construction of 8 different bond groups. We can see from Table 2 that most bonds exhibit all three characteristics.

- Time to maturity

Time to maturity was calculated using January 1993 as reference date. Since our sample only includes bonds that were still being traded in 1996, the minimum time to maturity amounts to 4 years. We obtained 6 bond groups, using the official classification of the Bundesbank. Bonds with long times to maturity (more than 15 years) are rare, Table 2 indicates that most bonds mature within 4 to 7 years.

¹⁵ Total market volume at the end of 1995 as estimated by the BVI (German Association of Investment Companies) was DM 43 billion. For further details, see BVI (1996).

¹⁶ Detailed eligibility criteria are listed in the Bundesbank Act and Federal Insurance Act.

- Type of issuer

We distinguish between public and private issuers. Public issuers are governments or government-sponsored organizations (e.g. European Investment Bank), while private issuers comprise mainly banks and industrial companies. Our sample contains an even distribution of bonds issued by private and public organizations.

We combine the different criteria to reflect our hypothesis that bonds with the same characteristics are considered to be equivalent. This way, we obtained a total of 222 bond groups¹⁷, which form the reference dataset for our analysis.

In order to evaluate which of the four criteria has the greatest impact on herding, we also applied the herding measures to datasets in which the bonds were grouped by only one criteria at a time.

¹⁷ Space constraints prevent us from showing a bond distribution table similar to Table 2.

Table 2 – Categorization of bonds

Nominal interest rate	Number of bonds	Type of quality	Number of bonds	Time to maturity	Number of bonds	Type of issuer	Number of bonds
Zerobonds	9	None	100	4 < 6	469	Private	851
0.01 – 3.00%	1	Collateral (1)	2	6 < 8	532	Public	824
3.01 – 3.50%	10	Cover fund (2)	26	8 < 10	370		
3.51 – 4.00%	19	Gilt-edged (3)	6	10 < 15	294		
4.01 – 4.50%	35	1 + 2	30	15 < 20	5		
4.51 – 5.00%	88	1 + 3	8	> 20	5		
5.01 – 5.50%	148	2 + 3	43				
5.51 – 6.00%	240	1 + 2 + 3	1460				
6.01 – 6.50%	347						
6.51 – 7.00%	210						
7.01 – 7.50%	112						
7.51 – 8.00%	138						
8.01 – 8.50%	146						
8.51 – 9.00%	74						
9.01 – 9.50%	2						
Floating rate	96						

4.3 MEASURES OF HERDING

As discussed earlier in section 3.2, it is necessary to distinguish between excess herding and benchmark herding. We use the measure H as defined in Lakonishok et al. (1992) to explore evidence of excess herding. In order to capture market-wide herding, we follow Oehler (1998) and calculate HF and HV.

The benchmark value, i.e. the expected value under the null hypothesis of no herding, is already incorporated in the H measure through the adjustment factor AF. For HF and HV it is necessary to define a benchmark as¹⁸

$$BM = \left| \frac{c_B - c_S}{c_B + c_S} \right|$$

where χ_B is the probability of a mutual fund (trading volume) being a buyer (buying volume) and χ_S the probability of a mutual fund (trading volume) being a seller (selling volume).

4.4 HYPOTHESES

We have seen in section 3.3 that evidence of herding depends on the type of herding that is studied. The findings of Lakonishok et al. (1992), Grinblatt et al. (1995), Wylie (1998), Oehler (1998), and Wermers (1999) suggest that there is only weak evidence of excess herding in stock markets. Following these studies, *we expect to find no evidence of excess herding in our dataset (Hypothesis 1)*.

Market-wide herding, however, seems to be a relevant phenomenon in stock markets. The same should hold true for bond markets and *we therefore expect our herding measures to detect market-wide herding in our sample (Hypothesis 2)*.

Bonds exist in a larger number and a bigger variety than stocks and we account for this fact through our categorization of bonds. Yet even with the formulation of bond groups, the universe of bonds remains relatively large compared to stocks. *Hence, we believe that the level of market-wide herding in bond markets is lower than in stock markets (Hypothesis 3)*.

5. RESULTS

5.1 TRANSACTION VOLUMES AND ACTIVITY LEVELS

It should be noted at the outset that there are two possible sources of distortion. Table 3 shows transaction volumes and activity levels for our sample grouped by nominal interest rate¹⁹. The transaction volume for a bond group in a particular period is the total number of buy and sell transactions, while the activity level indicates the number of different mutual funds that have been active²⁰.

We can see from Table 3 that for some bond groups the transaction volume in a period equals one, which means that there has only been one transaction. Of course, the activity level must be one as well. Calculating HF and HV then yields values of one, suggesting strong evidence of herding when in fact there has only been one mutual fund active. Low transaction volumes are therefore a source of distortion and lead to an upward bias, overstating the degree of herding.

Furthermore, some bond groups have an activity level of one but a transaction volume larger than one. This is possible, because bond groups might comprise bonds in which the same

¹⁸ See Oehler (1998).

¹⁹ Transaction volumes and activity levels for bonds grouped by type of quality, time to maturity, and type of issuer are presented in the appendix.

²⁰ The maximum activity level is 26, the total number of mutual funds in our sample.

mutual fund has been active²¹. In such cases, values for HF and HV can also be misleading, and the magnitude and direction of distortion depend on the actual mutual fund behavior. Low activity levels are hence another source of distortion.

We account for low transaction volumes by first calculating HF and HV for the original dataset. Then we exclude all bond groups and periods with transaction volumes of less than two and five, respectively. Values for HF and HV should be lower and reveal the extent of the upward bias.

It is difficult to eliminate the second source of distortion. However, unreported regression analysis show that activity levels and transaction volumes are strongly correlated. By imposing minimum transaction volumes we therefore simultaneously mitigate the effects of low activity levels.

5.2 EXCESS HERDING

Our results regarding excess herding are presented in Table 4. As we can see, the mean value of the herding measure H across all 222 bond groups and all periods amounts to 0.026. This value coincides with the findings in previous studies and confirms Hypothesis 1. There is only weak evidence of excess herding in bond markets.

Note that the results differ when we group bonds by only one criteria at a time. Table 4 shows that almost no excess herding can be measured when we group bonds by type of quality, time to maturity, or type of issuer. Nominal interest rate, however, appears to be a determinant of excess herding. The mean value of H across all 16 nominal interest rate groups and all periods is 0.118, which is surprisingly large. In order to analyze the reasons for this phenomenon, we have summarized the values of H for every nominal interest rate group in Table 5. Apparently, excess herding is most relevant for bond groups with either relatively low or relatively high nominal interest rates. A possible explanation might be that the number of bond issues with low or high nominal interest rates is limited, so that mutual funds interested in purchasing low/high interest rate bonds are faced with essentially the same choice. Herding in bonds with high nominal interest rates can also be explained by the term structure of interest rates. Figure 1 shows that interest rates were rapidly declining since 1990.

5.3 MARKET-WIDE HERDING

5.3.1 OVERALL RESULTS

Table 6 shows our results for market-wide herding across all 222 bond groups. Values for HF and HV have been calculated on the original dataset and on datasets with minimum transaction volumes of two and five, respectively. T-statistics are presented in parentheses. Benchmark values for HF and HV under the null hypothesis are virtually zero in all periods.

We can see that the values of HF for the original dataset vary between 0.751 and 0.862 and the average value across all periods is 0.805. HV values are even higher in every period, ranging from 0.817 to 0.909. The average HV value across all periods is 0.862. Apparently, herding amplifies trading volumes. The T-statistics show that our results are significant at the 99% confidence level. Clearly, there is strong evidence of market-wide herding, which confirms Hypothesis 2.

²¹ For example, the floating rate bond group generally has high transaction volumes, but low activity levels. The reason is that our sample contains a few mutual funds that specialize on floating rate bonds.

Table 3 – Transaction volumes and activity levels for bonds grouped by nominal interest rate

	1/93-6/93		7/93-12/93		1/94-6/94		7/94-12/94		1/95-6/95		7/95-12/95	
	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl
Zerobonds	4	4	6	5	2	1	0	0	1	1	1	1
0.01 – 3.00%	0	0	0	0	0	0	0	0	0	0	1	1
3.01 – 3.50%	0	0	0	0	0	0	0	0	1	1	9	1
3.51 – 4.00%	0	0	0	0	0	0	0	0	3	0	20	3
4.01 – 4.50%	0	0	1	1	10	4	6	1	17	7	28	10
4.51 – 5.00%	0	0	35	12	29	11	19	6	33	12	44	13
5.01 – 5.50%	2	1	54	20	47	14	37	10	61	19	79	20
5.51 – 6.00%	46	16	104	21	45	17	49	15	106	22	137	22
6.01 – 6.50%	127	21	119	21	48	15	60	19	141	22	169	21
6.51 – 7.00%	70	19	38	16	30	13	61	18	96	19	94	19
7.01 – 7.50%	44	15	25	12	11	6	46	12	37	9	33	10
7.51 – 8.00%	45	12	41	13	11	7	13	6	33	9	41	15
8.01 – 8.50%	43	13	57	16	21	8	16	6	21	9	48	10
8.51 – 9.00%	29	12	23	10	15	6	11	4	7	5	21	7
9.01 – 9.50%	1	1	0	0	0	0	0	0	0	0	1	1
Floating rate	44	8	51	4	46	5	60	5	59	6	52	1

TrnsVol = Transaction volume, ActLvl = Activity level

Table 4 – Mean values of herding measure H

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
222 bond groups	0.058	0.062	0.041	-0.020	0.008	0.017	0.026
Nominal interest rate	0.152	0.225	0.199	0.000	0.015	0.126	0.118
Type of quality	0.053	-0.050	-0.093	-0.061	-0.078	0.035	-0.036
Time to maturity	0.007	0.036	-0.060	-0.021	-0.031	0.029	-0.007
Type of issuer	0.043	0.023	-0.027	0.013	-0.038	-0.010	0.001

Table 5 – Detailed overview of herding measure H for bonds grouped by nominal interest rate

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
Zerobonds	0.053	0.112	0.070	n/a	0.000	0.072	0.061
0.01 – 3.00%	n/a	n/a	n/a	n/a	n/a	0.000	0.000
3.01 – 3.50%	n/a	n/a	n/a	n/a	0.000	0.240	0.120
3.51 – 4.00%	n/a	n/a	n/a	n/a	0.115	0.297	0.206
4.01 – 4.50%	n/a	0.000	0.210	0.205	0.020	0.207	0.128
4.51 – 5.00%	n/a	0.293	0.222	-0.015	0.060	0.073	0.127
5.01 – 5.50%	-0.374	0.322	0.237	-0.013	-0.089	0.020	0.017
5.51 – 6.00%	0.215	0.282	0.142	-0.070	0.051	0.075	0.116
6.01 – 6.50%	0.198	0.018	0.097	-0.054	-0.066	-0.053	0.023
6.51 – 7.00%	0.113	0.157	0.157	0.037	-0.052	-0.046	0.061
7.01 – 7.50%	-0.106	0.374	0.236	0.090	-0.120	0.160	0.106
7.51 – 8.00%	0.439	0.376	0.327	-0.211	0.060	0.345	0.223
8.01 – 8.50%	0.487	0.415	0.305	0.151	-0.031	0.424	0.292
8.51 – 9.00%	0.458	0.407	0.364	-0.040	0.330	0.222	0.290
9.01 – 9.50%	0.209	n/a	n/a	n/a	n/a	0.000	0.104
Floating rate	-0.019	-0.057	0.020	-0.085	-0.071	-0.028	-0.040

n/a indicates that no transaction has occurred.

Figure 1 – Term structure of interest rates in Germany

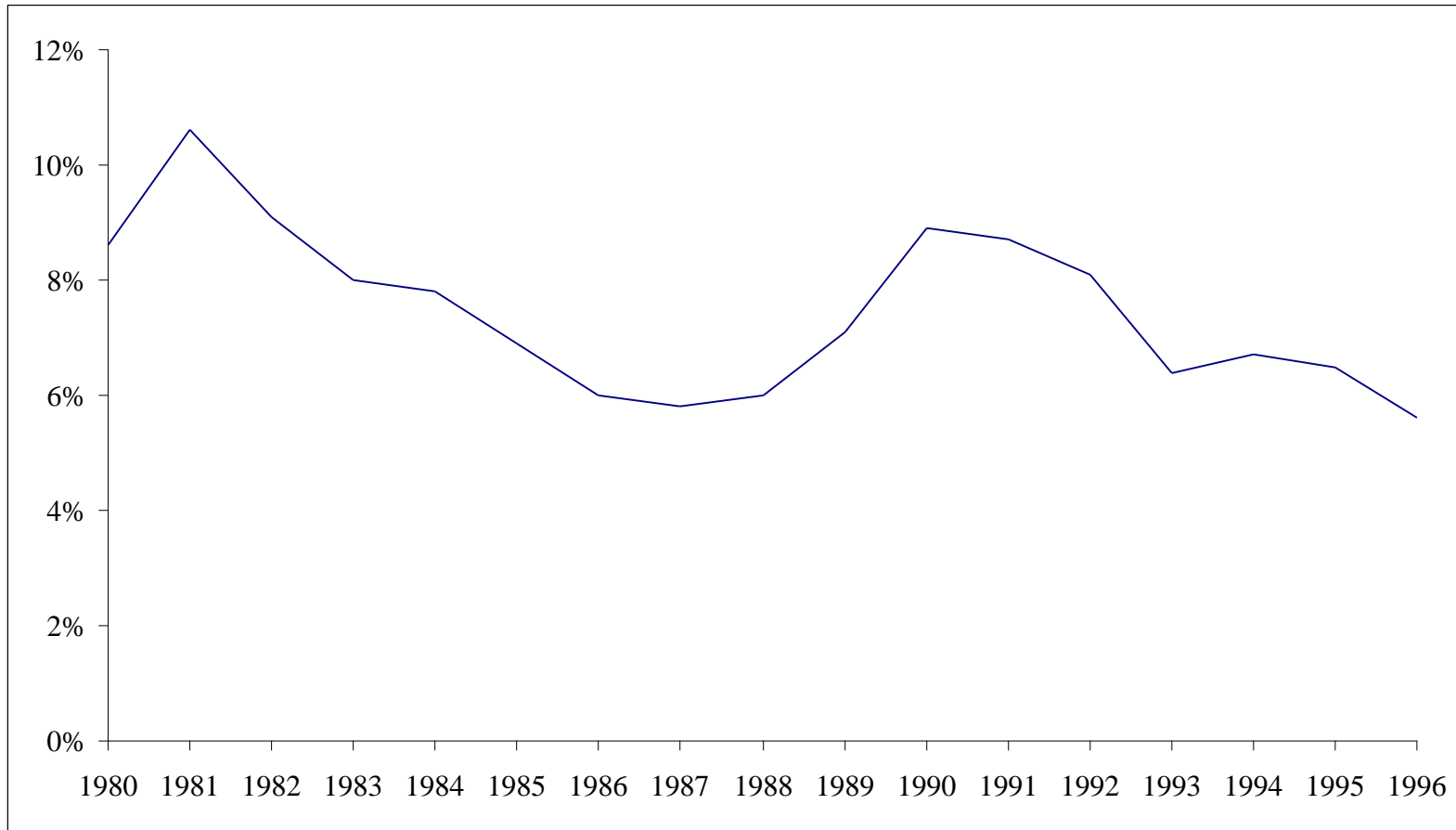


Table 6 – Mean values of herding measures HF and HV for all 222 bond groups

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
Original dataset (minimum transaction volume = 1)							
HF	0.862 (28.728)	0.840 (28.934)	0.842 (27.599)	0.751 (21.163)	0.767 (26.130)	0.790 (28.621)	0.805 (64.689)
HV	0.909 (41.304)	0.892 (40.230)	0.879 (31.504)	0.833 (30.285)	0.817 (32.568)	0.857 (38.873)	0.862 (85.638)
Minimum transaction volume = 2							
HF	0.796 (18.862)	0.766 (19.233)	0.748 (16.729)	0.573 (11.459)	0.619 (15.397)	0.688 (18.594)	0.697 (40.078)
HV	0.866 (27.647)	0.843 (27.278)	0.806 (19.189)	0.713 (17.384)	0.700 (19.753)	0.786 (25.831)	0.785 (54.361)
Minimum transaction volume = 5							
HF	0.759 (13.007)	0.816 (17.754)	0.680 (10.572)	0.400 (7.564)	0.432 (9.220)	0.690 (16.678)	0.637 (27.740)
HV	0.818 (16.162)	0.854 (21.069)	0.739 (10.926)	0.583 (11.135)	0.496 (9.971)	0.728 (17.488)	0.707 (32.739)

T-statistics are presented in parentheses. All results are significant at the 99% confidence level.

However, the HF and HV values are surprisingly large. In fact, they exceed the values Oehler (1998) calculated in his stock market study²². This suggests that herding in bond markets is stronger than in stock markets, which contradicts our Hypothesis 3. One possible explanation for this discrepancy are the two sources of distortion discussed in section 5.1 that potentially lead to an overstatement of the level of herding. Table 6 also presents the values of HF and HV when we impose hurdles on minimum transaction volumes. HF values range from 0.573 to 0.796 when the minimum number of transactions is two; the average value across all periods is 0.697. Values of HV are lower as well, the average value across all periods is 0.785 and the values vary between 0.700 and 0.866. When at least five transactions must have occurred, HF and HV values continue to decrease. The average HF value across all periods is 0.637, the corresponding HV value is 0.707. All values are significant at the 99% confidence level.

These findings confirm that low activity levels and low transaction volumes lead to an upward bias. Accounting for this bias, we find that the level of market-wide herding in bond markets is in fact lower than in stock markets. We therefore accept Hypothesis 3.

5.3.2 RESULTS BY BOND CRITERIA

Although the four criteria we selected are all important characteristics of bonds, mutual funds do not necessarily place an equal weight on them. It is reasonable to assume, for example, that nominal interest rates are most important, whereas the type of issuer is less relevant. If mutual funds are more influenced by certain bond characteristics than by others, we would expect herding to be more pronounced with regard to these characteristics. In order to shed light on this issue, we grouped the bonds by only one criteria at a time and calculated HF and HV for these datasets. The following sections present our results.

5.3.2.1 NOMINAL INTEREST RATE

From Table 7 we see that nominal interest rates indeed have a large impact on herding. The HF values for the original dataset are between 0.344 and 0.767, with an average value of 0.610 across all periods. HV values are similarly high, the spread is between 0.429 and 0.802 and the average value is 0.670. Further analysis show that the results are overstated due to low transaction volumes and low activity levels. When we exclude all nominal interest rate groups and periods with less than two transactions, the average HF value is 0.571 and the average HV value is 0.636. Imposing a hurdle of five transactions further decreases HF and HV values to 0.560 and 0.629. All values are significant at the 99% confidence level.

In order to better understand why herding is influenced so much by nominal interest rates, we summarized HV values for every nominal interest rate group and every period in Table 8. It appears that bonds with low and high nominal interest rates are most susceptible to herding. These results correspond with our findings in section 6.2, and low market liquidity and the term structure of interest rates again provide possible explanations for mutual funds' proclivity for bonds with low/high nominal interest rate.

5.3.2.2 TYPE OF QUALITY

Herding measures for bonds grouped by type of quality are presented in Table 9. HF values for the original dataset range from 0.220 to 0.664, the average value across all periods is 0.444. Imposing hurdles on transaction volumes leads to average HF values of 0.382

²² HF values range between 0.67 and 0.80, while the spread for HV values is between 0.78 and 0.85.

(minimum of two transactions) and 0.314 (minimum of five transactions). Values of HV vary between 0.202 and 0.747 when calculated for the original dataset. The average HV value is 0.560 and decreases to 0.511 and 0.464 in the presence of minimum transaction volumes. The results suggest that there is some evidence of market-wide herding when we group bonds by type of quality.

Table 10 provides detailed information about HV values for each type of quality group. Apparently, mutual funds herd less in bonds which possess all three quality characteristics and are thus most secure. Recall from section 4.2 that the vast majority of bonds has all three quality characteristics, so herding with regard to type of quality is mainly prevalent in a few more risky bonds.

Although there is some evidence of market-wide herding, the values of HF and HV are lower than in the previous section. This suggests that type of quality does play a role, but to a lesser extent than nominal interest rate.

5.3.2.3 TIME TO MATURITY

Results for time to maturity are shown in Table 11. The range of HF values for the original dataset is from 0.257 to 0.472, the average value across all periods amounts to 0.370. HV values are higher and vary between 0.320 and 0.523, with an average value of 0.446. Accounting for the upward bias in the dataset gives average HF values of 0.265 and 0.220 and average HV values of 0.353 and 0.323. It seems that herding is less relevant when we group bonds by time to maturity. Analyzing HV values in detail, we see from Table 12 that herding mainly occurs in bonds with long times to maturity. This can be explained by the low number of bond issues with times to maturity that exceed 15 years.

5.3.2.4 TYPE OF ISSUER

Grouping bonds by type of issuer leads to the formulation of two bond groups for which transaction volumes and activity levels are very high²³. It is therefore not necessary to impose minimum transaction volumes, since no upwards bias is to be expected. Table 13 presents the results for the herding measures HF and HV.

The values of HF are relatively low, ranging from 0.075 to 0.247. The average value of 0.148 indicates that there is only weak evidence of market-wide herding. The results for HV confirm this suggestion, even if the values are slightly higher. The average HV value is 0.258 and the spread is from 0.155 to 0.417. Table 13 also shows HF and HV values for the two type of issuer groups. Herding is much more pronounced for bonds issued by private organizations, the average HF value for private issues is 0.239 compared to 0.056 for public issues. HV values indicate the same discrepancy. Intuitively, bonds issued by public organizations are considered to be less risky, since it is very unlikely that a government or a government-sponsored organization will default.

²³ See Table 16 in the appendix.

Table 7 – Mean values of herding measures HF and HV for bonds grouped by nominal interest rate

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
Original dataset (minimum transaction volume = 1)							
HF	0.704 (6.520)	0.767 (9.508)	0.759 (10.383)	0.344 (3.814)	0.446 (4.370)	0.643 (7.078)	0.610 (14.985)
HV	0.802 (8.695)	0.764 (7.632)	0.754 (9.023)	0.429 (5.148)	0.549 (5.443)	0.716 (8.737)	0.670 (17.175)
Minimum transaction volume = 2							
HF	0.675 (5.875)	0.746 (8.747)	0.759 (10.383)	0.344 (3.814)	0.354 (3.741)	0.561 (5.697)	0.571 (13.584)
HV	0.783 (7.853)	0.742 (6.933)	0.754 (9.023)	0.429 (5.148)	0.474 (4.638)	0.650 (7.089)	0.636 (15.578)
Minimum transaction volume = 5							
HF	0.719 (6.878)	0.746 (8.747)	0.738 (9.647)	0.344 (3.814)	0.295 (3.633)	0.561 (5.697)	0.560 (13.274)
HV	0.853 (14.491)	0.742 (6.933)	0.732 (8.294)	0.429 (5.148)	0.427 (4.306)	0.650 (7.089)	0.629 (15.316)

T-statistics are presented in parentheses. All results are significant at the 99% confidence level.

Table 8 – Detailed overview of herding measure HV for bonds grouped by nominal interest rate

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
Zerobonds	1.000	0.082	1.000	n/a	1.000	1.000	0.816
0.01 – 3.00%	n/a	n/a	n/a	n/a	n/a	1.000	1.000
3.01 – 3.50%	n/a	n/a	n/a	n/a	1.000	1.000	1.000
3.51 – 4.00%	n/a	n/a	n/a	n/a	1.000	1.000	1.000
4.01 – 4.50%	n/a	1.000	1.000	1.000	0.915	0.856	0.954
4.51 – 5.00%	n/a	1.000	0.842	0.498	0.177	0.768	0.657
5.01 – 5.50%	0.000	1.000	0.859	0.262	0.288	0.380	0.465
5.51 – 6.00%	0.960	0.965	0.708	0.225	0.628	0.448	0.656
6.01 – 6.50%	0.627	0.705	0.194	0.165	0.205	0.347	0.374
6.51 – 7.00%	0.860	0.135	0.682	0.364	0.236	0.186	0.411
7.01 – 7.50%	0.588	0.956	0.966	0.339	0.210	0.650	0.618
7.51 – 8.00%	0.982	0.948	1.000	0.311	0.112	0.952	0.717
8.01 – 8.50%	1.000	0.921	0.249	0.909	0.740	1.000	0.803
8.51 – 9.00%	1.000	1.000	1.000	0.412	1.000	0.806	0.870
9.01 – 9.50%	1.000	n/a	n/a	n/a	n/a	1.000	1.000
Floating rate	0.810	0.450	0.554	0.236	0.181	0.058	0.381

n/a indicates that no transaction has occurred.

Table 9 – Mean values of herding measures HF and HV for bonds grouped by type of quality

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
Original dataset (minimum transaction volume = 1)							
HF	0.664 (4.087)	0.445 (2.998)	0.449 (2.784)	0.460 (2.866)	0.220 (3.659)	0.488 (3.070)	0.444 (7.511)
HV	0.747 (4.239)	0.654 (5.395)	0.652 (5.870)	0.607 (3.982)	0.202 (3.932)	0.550 (3.902)	0.560 (9.998)
Minimum transaction volume = 2							
HF	0.664 (4.087)	0.445 (2.998)	0.358* (2.276)	0.244** (2.113)	0.220 (3.659)	0.402* (2.538)	0.382 (6.719)
HV	0.747 (4.239)	0.654 (5.395)	0.594 (5.302)	0.450* (2.726)	0.202 (3.932)	0.474 (3.366)	0.511 (9.035)
Minimum transaction volume = 5							
HF	0.664 (4.087)	0.223 (4.021)	0.287** (2.339)	0.244** (2.113)	0.201 (2.977)	0.283* (2.217)	0.314 (6.160)
HV	0.747 (4.239)	0.515 (4.345)	0.557 (5.199)	0.450* (2.726)	0.211 (3.550)	0.369 (3.210)	0.464 (8.122)

T-statistics are presented in parentheses. Results are significant at the 95%, 90%(*), and 85%(**) confidence level.

Table 10 – Detailed overview of herding measure HV for bond7s grouped by type of quality

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
None	0.860	0.296	0.449	0.104	0.270	0.313	0.382
Collateral (1)*	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Cover fund (2)	1.000	0.735	1.000	0.904	0.057	0.253	0.658
Gilt-edged (3)	n/a	1.000	0.333	1.000	0.143	1.000	0.695
1 + 2	0.818	0.860	0.809	0.693	0.016	0.285	0.580
1 + 3	n/a	1.000	1.000	1.000	0.398	1.000	0.880
2 + 3	1.000	0.403	0.646	0.500	0.245	0.820	0.602
1 + 2 + 3	0.057	0.283	0.324	0.051	0.282	0.175	0.196

n/a indicates that no transaction has occurred. * Bonds in this group were bought before 1993 and held throughout our sample period.

Table 11 – Mean values of herding measures HF and HV for bonds grouped by time to maturity

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
Original dataset (minimum transaction volume = 1)							
HF	0.399* (2.453)	0.472 (2.704)	0.298* (2.055)	0.357* (2.256)	0.257 (3.050)	0.439* (2.458)	0.370 (6.219)
HV	0.414* (2.364)	0.514 (3.122)	0.523 (4.422)	0.464 (2.727)	0.320 (4.462)	0.435* (2.383)	0.446 (7.656)
Minimum transaction volume = 2							
HF	0.249* (3.075)	0.472 (2.704)	0.158 (3.517)	0.228** (2.025)	0.257 (3.050)	0.159 (4.687)	0.265 (5.684)
HV	0.268** (2.158)	0.514 (3.122)	0.427 (5.004)	0.357* (2.204)	0.320 (4.462)	0.152* (2.587)	0.353 (6.960)
Minimum transaction volume = 5							
HF	0.249* (3.075)	0.367* (2.151)	0.158 (3.517)	0.228** (2.025)	0.135* (2.487)	0.159 (4.687)	0.220 (5.366)
HV	0.268** (2.158)	0.417* (2.561)	0.427 (5.004)	0.357* (2.204)	0.258 (3.895)	0.152* 2.587	0.323 6.506

T-statistics are presented in parentheses. Results are significant at the 95%, 90%(*), and 85%** confidence level.

Table 12 – Detailed overview of herding measure HV for bonds grouped by time to maturity

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
4 < 6	0.404	0.121	0.419	0.286	0.285	0.097	0.269
6 < 8	0.549	0.169	0.428	0.207	0.430	0.025	0.301
8 < 10	0.058	0.255	0.164	0.063	0.124	0.189	0.142
10 < 15	0.060	0.539	0.422	0.242	0.193	0.298	0.292
15 < 20	n/a	1.000	1.000	1.000	0.276	1.000	0.855
> 20	1.000	1.000	0.704	0.987	0.610	1.000	0.884

n/a indicates that no transaction has occurred.

Table 13 – Herding measures HF and HV for bonds grouped by type of issuer

	1/93-6/93	7/93-12/93	1/94-6/94	7/94-12/94	1/95-6/95	7/95-12/95	Average
Mean values							
HF	0.247 (1.263)	0.163 (1.134)	0.140 (1.826)	0.142 (1.612)	0.119* (7.949)	0.075 (1.244)	0.148* (1.609)
HV	0.238 (2.125)	0.312 (2.690)	0.417 (3.552)	0.155 (1.194)	0.272* (7.451)	0.155 1.085	0.258* (2.390)
Herding measure HF by type of issuer group							
Private	0.443	0.306	0.216	0.231	0.104	0.135	0.239
Public	0.051	0.019	0.063	0.054	0.134	0.015	0.056
Herding measure HV by type of issuer group							
Private	0.350	0.427	0.535	0.285	0.308	0.297	0.367
Public	0.126	0.196	0.300	0.025	0.235	0.012	0.149

T-statistics are presented in parentheses. * indicates significance at the 85% confidence level; all other results are insignificant.

6. CONCLUSION

This study aims at analyzing institutional herding in the German bond market. With regard to the large number of bonds, we categorize bonds according to four different criteria and study the investment behavior of mutual funds in these bond groups. Our results closely mirror the findings of previous studies in the stock market. We find that there is only weak evidence of excess or bond-picking herding, while market-wide herding appears to be a relevant phenomenon. However, the degree of herding is lower than in the stock market, which can be attributed to the big variety of bonds that remains despite our categorization. Detailed analysis suggests that the nominal interest rate is the most important bond characteristic to mutual funds. Type of quality and time to maturity also seem to play a role in the bond selection process, but only to a lesser extent. The type of issuer seems to be irrelevant.

The time period of our study is also relatively short and only allows us to indicate a trend. This limitation is further exacerbated by the low frequency of portfolio data (semi-annual portfolio holdings) and the necessity to substitute changes in portfolio holdings for trading data. A more comprehensive sample over a longer period of time should provide more differentiated evidence of herding.

APPENDIX**Table 14 – Transaction volumes and activity levels for bonds grouped by type of quality**

	1/93-6/93		7/93-12/93		1/94-6/94		7/94-12/94		1/95-6/95		7/95-12/95	
	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl
None	40	13	57	16	37	9	35	10	43	11	46	12
Collateral (1)*	0	0	0	0	0	0	0	0	0	0	0	0
Cover fund (2)	5	3	7	6	4	1	5	4	10	5	15	7
Gilt-edged (3)	0	0	4	4	2	1	1	1	3	3	3	1
1 + 2	10	5	13	8	11	1	14	5	19	5	16	5
1 + 3	0	0	3	1	1	0	1	1	5	3	1	1
2 + 3	13	7	5	4	5	4	8	3	10	5	25	8
1 + 2 + 3	387	24	465	25	255	26	314	25	526	26	672	26

TrnsVol = Transaction volume, ActLvl = Activity level. * Bonds in this group were bought before 1993 and held throughout our sample period.

Table 15 – Transaction volumes and activity levels for bonds grouped by time to maturity

	1/93-6/93		7/93-12/93		1/94-6/94		7/94-12/94		1/95-6/95		7/95-12/95	
	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl
4 < 6	100	17	133	23	74	15	128	21	187	20	179	21
6 < 8	115	22	133	22	101	14	114	19	196	23	213	23
8 < 10	118	20	138	21	52	17	66	17	86	18	218	22
10 < 15	121	20	142	20	79	18	63	14	139	19	166	23
15 < 20	0	0	2	1	1	1	1	1	4	4	1	1
> 20	1	1	6	6	8	7	6	4	4	4	1	1

TrnsVol = Transaction volume, ActLvl = Activity level

Table 16 – Transaction volumes and activity levels for bonds grouped by type of issuer

	1/93-6/93		7/93-12/93		1/94-6/94		7/94-12/94		1/95-6/95		7/95-12/95	
	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl	TrnsVol	ActLvl
Private	183	24	242	25	125	23	156	18	288	23	370	24
Public	272	23	312	25	190	25	222	24	328	26	408	25

TrnsVol = Transaction volume, ActLvl = Activity level

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