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Institutional herd behaviour in stock and bond markets

An analysis of potentially irrational investment patterns

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, second reader, Erasmus School of Economics or Erasmus University Rotterdam.

ABSTRACT

This paper examines the extent to which institutional investors in the U.S. market herd in the trading of various securities in a period between 2004 and 2019. The findings indicate that investors herd more around both stocks and bonds, though the magnitude of herding is higher for bonds than it is for stocks. The difference in magnitude is substantial and shows opposing trends as activity levels increase. Herding shows varying drivers depending on trading activity, and the security in question. Stocks appear to be principally driven by buy-side market herding while the bond-market herding varies in driver seemingly based on activity level.

Keywords: Herding; Institutional investors; bonds; stocks

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CHAPTER 1: Introduction

Since the 1980s, and picking up pace in the 1990s, the field of finance and asset pricing started to diverge from the classical perspective of market participants acting rationally in the face of market conditions. Up until that point, most of the theory around asset pricing was fundamentally tied to the principle that a vast majority of, if not all, investors are rational in the manner in which they process information and act upon it. The decade of the 1990s saw the advent of behavioral finance, a movement in the broader field of financial studies and asset pricing, that acknowledged the possibility that market participants may not be rational decision-makers and asset prices may not be exclusively a reflection of efficient market participants taking rational decisions founded on publicly available information (Hirshleifer, 2015). A myriad of different hypotheses came to light during the last three decades, all meriting an expansive body of work.

One of the areas of research, initially introduced by Bikhchandani, Hirshleifer & Welch (1992), was the idea that asset prices may reflect a consensus amongst market participants or the imitation of activities from influential market participants by other investors. The result is the correlation of trades among investors which would then result in systemic error and irrational asset pricing (Chen, 2013). This would go on to be labeled as 'herd behaviour' or 'herding', a denomination derived from the phenomenon documented in the study of animals. 'Herding' and its surrounding study came to provide a point of merger between psychological analysis of individual agents as well as the analysis of non-rational actors in the market and their economic effect.

This study strays away from the 'deeper' levels of both the observational and payoff hierarchies and focuses not on the intentionality behind herd behaviour, but on identifying its presence, and its direction and magnitude. Departing from the framework established by Cai et al. (2019), we initially analyse herd behaviour in the U.S. corporate bond market by institutional investors. Establishing, first, the magnitude of the potential effect in the bond market. Subsequently, a similar analysis is performed on the various U.S. stock markets, this builds upon the works of Brown et al. (2014), which itself builds on Wermers (1999) analysis of herding by investment funds in the various American stock markets. The inclusion of both bond markets and stock markets presents an opportunity to provide a more complete assessment of herd behaviour in financial markets and across asset classes. This crossclass analysis is also of interest given it provides a further opportunity to understand fund behaviour as related to the idiosyncratic differences between different types of assets. All leading to the question: is institutional herd behaviour a present phenomenon in financial markets, and what is the nature of herding across asset classes?

This study will examine whether investment funds herd in their trades. To measure herding by funds, the quarterly equity holdings of available funds between 2004 and 2019 are analyzed. Following the Lakonishok et al. (1992) measure of herding which examines the proportion of funds trading a given asset that are buyers. If funds evidence large imbalances between the number of buyers and sellers they can be considered as exhibiting herd behaviour. Subsequently, to measure the potential presence of herding, assets are identified to have at least five trades of a given security during a given quarter. The identified assets are then divided into those having a larger proportion of buyers and those having a larger proportion of sellers. Then the herding measure is calculated for each group.

The hypothesis presented in this paper is that investment funds converge in their trading behaviour, consistent with the phenomenon of herding, which should be evidenced by the use of the herding metric developed by Lakonishok et al. (1992). It is expected of this behaviour to relate asset specific differences which may speak to both an idiosyncratic and regulatory difference in the fund's environment. Consistent with the literature, we expect to see a clearer herding pattern in the bond market than that seen in the various stock markets. Furthermore, it is expected that herding will not be evenly distributed between buying and selling of securities and that there will be idiosyncratic differences in the present fund behaviour relating to the nature of the asset and overall market activity. This study, however, fails to provide a causal explanation for the phenomenon of herding and will be limited to attempting to provide further evidence as to the existence of the phenomenon as a whole and its specific presentation. It is left to the wider field of behavioural finance, asset pricing, and psychology to continue to pursue a causal explanation for herd behaviour.

CHAPTER 2: Theoretical Underpinnings

This paper touches upon various strands of financial, behavioural, and economic research. It is, first and foremost, an analysis of the behavioural phenomenon of 'herding'. This section elaborates upon the existing literature and the theoretical aspects that form the foundation for this paper.

2.0 Herd Behaviour

The concept of herd behaviour as a descriptor of human behaviour can be traced as far back as to the XIX century, philosophers Søren Kierkegaard and Friedrich Nietzsche. The concept was used by Keynes (1936), even if the term of 'herding' was never explicitly stated in his explanation of imitative individual behavior. The concept, as modernly understood, did not find the light of day until the second half of the XX century when it became the focal point of evolutionary biology, as per Hamilton (1971). It was not until 1990 that, as a part of the broader concurrent study of market behaviour and decision-making, the concept of herd behaviour emerged as an economic point of interest (Scharfstein & Stein, 1990). The seminal works are published in 1992 which provide the footing upon which research is to be carried out moving forward (Banerjee, 1992; Bikhchandani et al., 1992; Lakonishok et al., 1992). For the purposes of this paper, herd behaviour is to be understood as the consensus amongst market participants or the imitation of activities from influential market participants by other investors (Bikhchandani et al., 1992).

The nature of herding has long been a point of interest for theorists, of particular interest, and the subject of much debate, has been the mechanistic understanding of the phenomenon. Though the literature on this subject on a theoretical level is as vast as it is complex, this paper aims to provide a condensed portrayal of the theoretical understanding behind herd behaviour. In a simplified form, models around herding fall into two camps differentiated by their predictions on price dynamics. The first camp theorizes that economic agents ignore any private information they may hold and imitate the observed behaviour of other agents. The second camp, on the other hand, theorizes that herding is the result of the individual analysis of economic fundamentals and is a natural part of the price discovery process (Cai et al., 2019; Hirshleifer & Hong Teoh, 2003).

Theories around the underlying reason for herding are varied but can be succinctly categorized into those that fall under observational hierarchy, describing the first camp, and payoff hierarchy, describing the second camp. Figure 1 provides a visual representation of the double hierarchy of herding; it is a simplified version of the one used by Hirshleifer & Hong Teoh (2003). Herding being the most inclusive category, within it lie rectangles depicting the observational hierarchy and ovals depicting the payoff hierarchy.

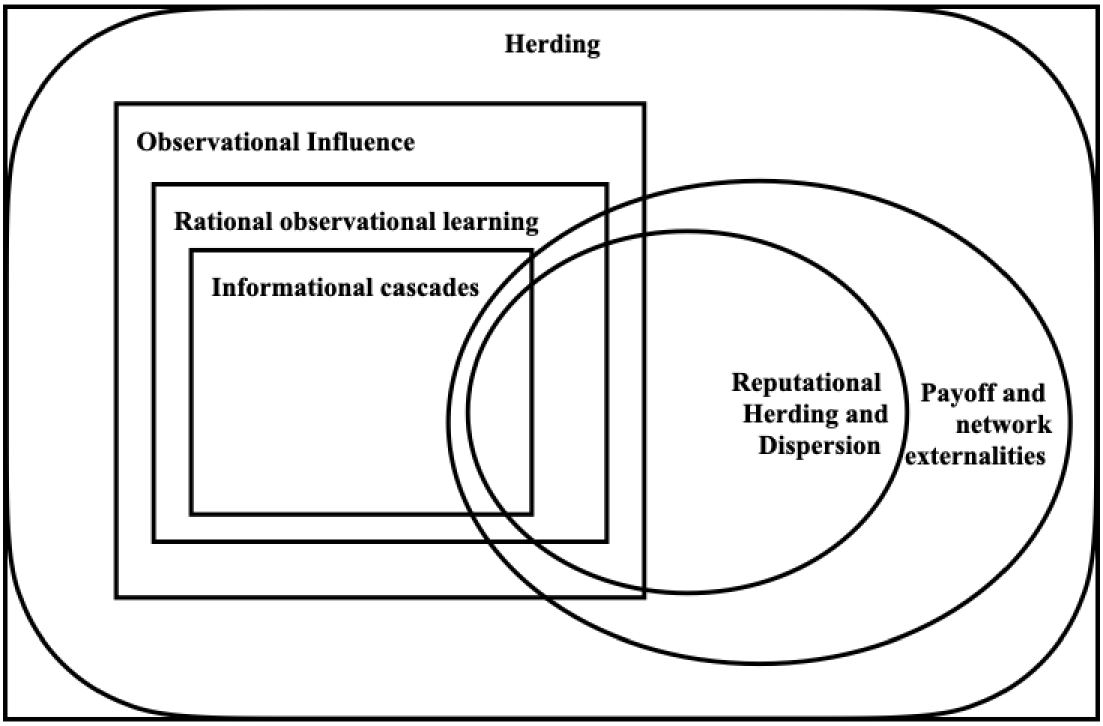


Figure 1: Herding hierarchies (Hirshleifer & Hong Teoh, 2003)

2.1 Observational Hierarchy

The observational hierarchy describes the source of the information upon which herding is based on. As the name implies, the observational hierarchy encompasses herding that results from the observation of other market participants. The observation of other market participants' observed behaviour, or results of said behaviour, can encompass both rational and irrational decision making by the observer. Observational decision-making may, therefore, be classified as imperfectly rational. The observational hierarchy is conditioned upon the basis of ignoring, usually rationally, private information and the imitation of others. Herding that occurs as a result of observational influence generally results in market inefficiencies and excess price volatility. The underlying mechanism may include imperfect information, reputational concern, and benchmark-based compensation structures (Cai et al., 2019). However, archival data cannot observe whether economic actors make use of private information or not.

2.1.1 Rational Observational Learning

Within the observational hierarchy lies the observational influence resulting from Bayesian inferences made from the behaviour, or results, of other's actions. Rational observational learning is often used as the mechanistic explanation for herd behaviour by rational actors. It is suggested that imitation may be rational as it may offer the observer the ability to exploit information possessed by others about the market. Even if imitation is reached by means other than rational analysis, the predisposition to imitate others may be well in accord with to costs and benefits through the guidance of natural selection (Hirshleifer & Hong Teoh, 2003).

2.1.2 Informational Cascades

Informational cascades have been described as a specific form of rational observational learning (Hirshleifer & Hong Teoh, 2003) or a phenomenon distinct, but connected, to herding (Bikhchandani et al., 1992). The latter suggests that herding is the result of informational cascades. To be specific, informational cascades can be understood as observational learning in which the observation of other economic actors is informative to the point of making the actions of the observer not depend on their own private signal. In this scenario imitation will certainly occur, it will, however, not be informative to subsequent observers.

2.2 Payoff Hierarchy

The payoff hierarchy, contrary to the observational hierarchy, suggests that herding is the result of an economic agent's actions influencing the payoffs of other agents. The fundamental reasoning behind the payoff hierarchy is not all that different from what has been observed in the field of biology. Hamilton's (1971) analysis of the 'selfish herd' suggests that the clustering of prey animals is an indirect outcome of the selfish attempts of individual animals to protect themselves from predators by putting other individuals in between themselves and the predator. Herd behaviour can, therefore, be characterized as a byproduct of externalities. In economics, externalities are the focus of much attention and financial economists have, much like other economists, dedicated extensive time and resources to the better understanding of their effects on economic outcomes. Tangentially related to the study of herding then lie the study of payoff externalities, such as Diamond & Dybvig's (1983) bank run model. Similarly, Admati and Pfleiderer's (1988) theory of volume clumping is underlined by the payoff interactions induced by the economic incentive of uninformed investors to trade with other uninformed investors instead of informed ones.

2.2.1 Reputational Herding and Dispersion

The convergence, or possibly divergence, of behaviour can be based on individual efforts to maintain good reputational standing with other economic agents. The desire to maintain said standing may cause payoff interactions, as suggested by the literature (Brandenburger & Polak, 1996; Rajan, 1994;

Scharfstein & Stein, 1990; Trueman, 1994; Zwiebel, 1995). Reputational herding is of particular interest as it provides an avenue for multidisciplinary analysis, given it both speaks to the field of psychology and neuroscience as well as economics (Bobe & Piefke, 2019).

2.3 Limitations and Subsequent Research

The subject of herding remains of much interest to an increasingly diverse set of researchers however, some of the fundamental struggles remain in place. The primordial impediment is the inability to derive a conclusive tie between the observable phenomenon of herding and the underlying reasoning used to explain it. The expansion of the field has also allowed for increased specificity in the analysis of the phenomenon, leading to more specific phenomenological analysis. It has allowed for the coinage of terms such as reverse cascades (Sgroi, 2003), antiherding, contrarianism, nonherding (Lutje, 2009), and spurious herding (Fernández et al., 2011). It remains, however, a challenge at times to reconcile the myriads of discipline-specific explanations. Within the field of economics, the challenge now has been to provide more expansive proof of the phenomenon, expanding beyond stock market volume analysis and approaching other assets. The broader field of behavioural finance has continued to move in the direction of studying a larger set of asset types, particularly in the direction of financial instruments and derivatives (Hirshleifer, 2015).

CHAPTER 3 Data, Sampling, and Herding Measures

3.1 Data and Sampling

The data in this paper has been compiled from the Center for Research in Security Prices (CRSP). Data on institutional investor holdings, the initial dataset included all available security types, as used in (Cai et al., 2019) and (Becker & Ivashina, 2015), among others. This dataset is free of survivorship-bias and contains quarter-end security holdings for mutual funds, which will be referred to as "funds" or "institutions", throughout this paper. In alignment with the literature "trades" are defined as changes in funds' quarter-end holdings. A limitation of this definition is that quarter-end portfolio holdings are only a snapshot in time and cannot account for intra-quarter round-trip transactions. However, this impediment should not pose an impediment into this paper's ability to assert the presence of herding by funds, as has been shown in the literature (Cai et al., 2019; Wermers, 1999). An additional aspect of the sampling process was the exclusion of all bonds with a maturity date of less than a year to emphasize active trading decisions. All securities analysed are traded in the United States.

The sample selection is constructed covering the period from Q1 2004 to Q4 2019. Specifically, the sample is restricted to dollar-denominated securities for which a CUSIP is available and that are held by U.S. mutual funds. A fundamental part of the sample selection was limiting the selection to funds for which there is information available in Q1 2004 and Q4 2019, this decision was made for practical reasons relating to the practical limitations of having to effectively filter hundreds of millions of observations in the dataset. The implications of this decision will be discussed in the 'limitations' section of this paper. It bears mentioning that a single fund may have multiple portfolios that may buy and sell securities independently of one another.

3.2 Sample Statistics

The sample used consists of 6,053 unique investors with varying levels of activity over time. Figure 2 displays the number of active investors per quarter in the sample. The activity levels vary over time, but it is interesting to note that the highest and lowest level of unique investors lie around the onset of the 2008 financial crisis.

Figure 2: Number of unique investors per quarter

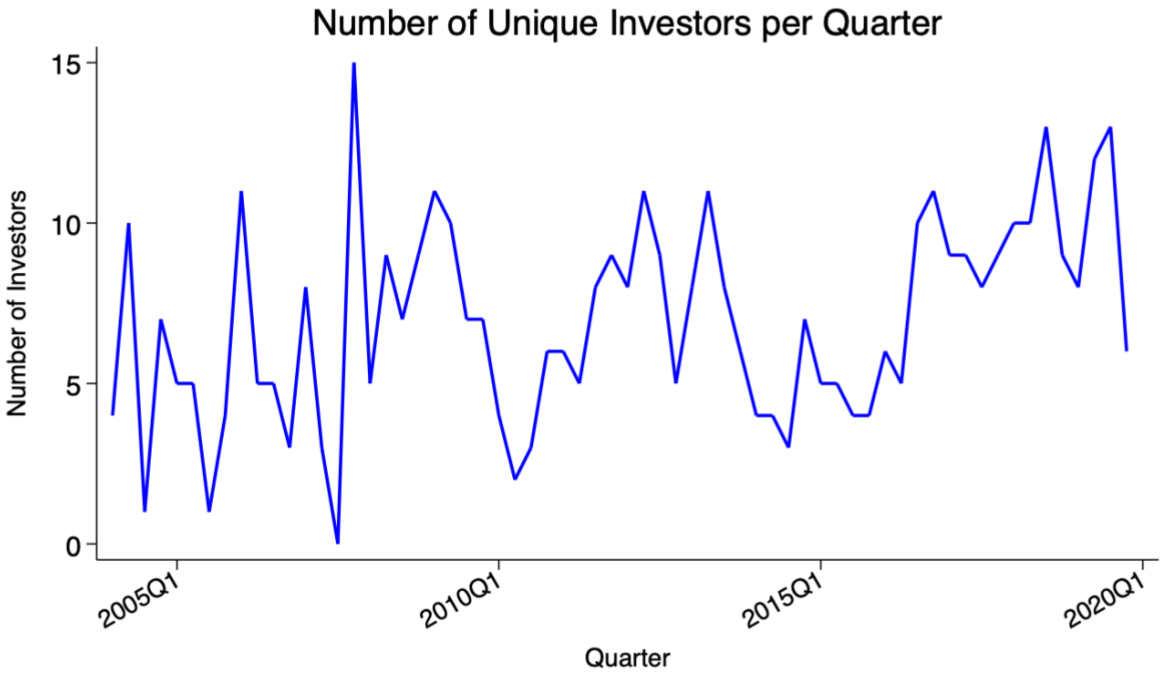
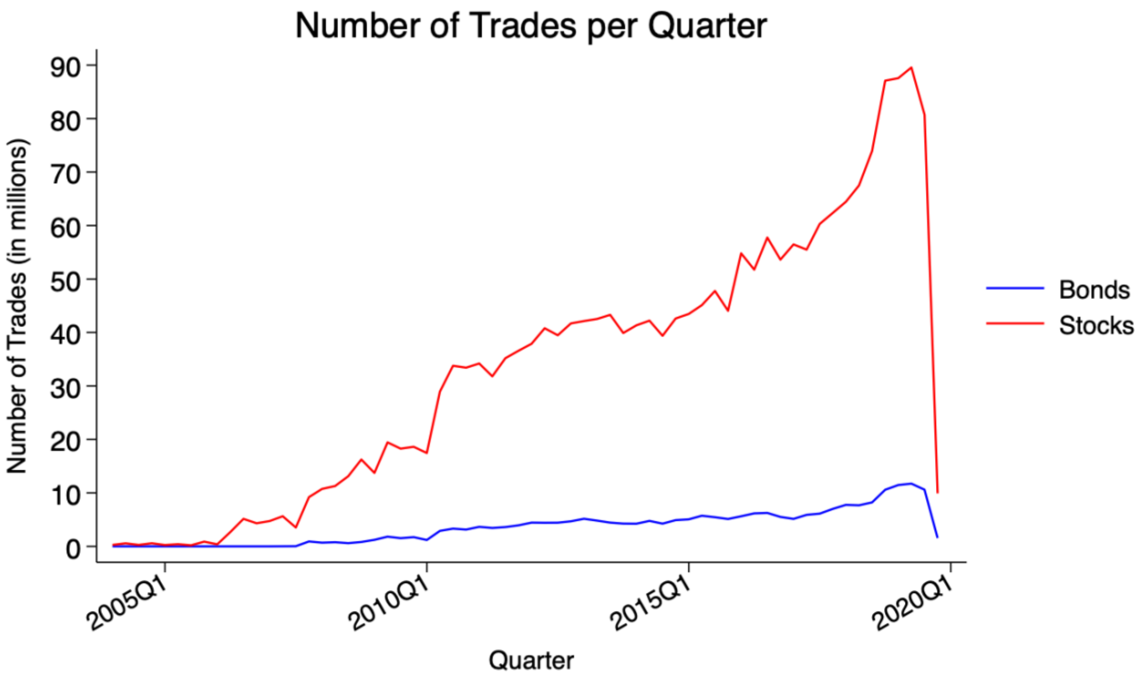


Figure 3 shows the level of trading activity per quarter, which shows clear growth in the number of trades over time. The number of stock trades per quarter are several orders of magnitude higher than the number of bond trades per quarter. The maximum level of trading activity is seen during Q2 2019 before a precipitous decline which may be attributed to the early signs of market uncertainty caused by the COVID-19 pandemic.

Figure 3: Number of trades per quarter (in millions)



The average investor conducts, on average, 135 transactions per quarter, of which 79 are transactions relating to stocks and 56 are related to bonds. Of said 79 transactions, 54 involve the increase of their position relative to the previous quarter, and 25 relate to the decrease in position relative to the previous quarter.

Table 1: Average investor profile, transactions per quarter (rounded to the nearest integer)

Security	Transactions	Purchases	Sales
Stocks	79	54	25
Bonds	56	28	28

CHAPTER 4 Method

In accordance with the literature, this paper adopts the herding measure widely used across the literature by (Lakonishok et al., 1992), referred to as LSV in this paper. The measure is designed to measure whether a disproportionate amount of funds is buying or selling a certain security a given security at a rate beyond the market trading intensity in a given period. The herding measure for each security-quarter. The herding measure, HM from this point forward, of security i in quarter t is defined as:

$$HM_{i,t} = \left|p_{i,t} - E\left[p_{i,t}\right]\right| - E\left|p_{i,t} - E\left[p_{i,t}\right]\right|$$

Where $p_{i,t}$ is the proportion of buyers to all active traders of security i in quarter t:

$$p_{i,t} = \frac{\#\ of\ Buy_{i,t}}{\#\ of\ Buy_{i,t} + \#\ of\ Sell_{i,t}}$$

The term $E[p_{i,t}]$ is the expected level of buying intensity. In accordance with previous studies, $E\left[p_{i,t}\right]$ is estimated with the buying intensity of the market denoted as $\bar{p}_t$:

$$\bar{p}_t = \frac{\sum_i \#\ of\ Buy_{i,t}}{\sum_i \#\ of\ Buy_{i,t} + \sum_i \#\ of\ Sell_{i,t}}$$

The HM equation, therefore, measures the variation of the trading pattern of security i from the general trading pattern of securities in quarter t. HM is, therefore, measuring of much of this variation is driven by disproportionate buying or selling by the group of investors under consideration.

Departing from the null hypothesis of no herding, all institutional investors make independent decisions, suggesting all securities have an equal probability of being bought in a given quarter. In other words, the null hypothesis implies that the number of times a security is bought in a given period follows a binomial distribution ($n = \#\ of\ Buy_{i,t} + \#\ of\ Sell_{i,t}$ and $p = E[p_{i,t}]$). The term $E|p_{i,t} - E[p_{i,t}]|$ is an adjustment factor to account for the fact that $|p_{i,t} - E[p_{i,t}]|$ is always greater than zero. To ensure that, under the null hypothesis, $HM_{i,t}$ is equal to zero, we use the adjustment factor. Therefore, a positive significant herding measure will be statistical evidence for institutional herding in American security markets. The time adjustment of factors allows to correct for macroeconomic externalities and other trading pattern adjustments in a given quarter.

Addressing more specifically the adjustment factor $E|p_{i,t} - E[p_{i,t}]|$, it is defined as

$$E|p_{i,t} - E[p_{i,t}]| = \sum_{k=0}^{I_{j,t}} \binom{I_{j,t}}{k} p^k (1 - p_t)^{I_{j,t}-k} \left| \frac{k}{I_{j,t}} - p_t \right|$$

Where k is the number of buyers, is binomially distributed with the probability of purchase intensity across a given security (stocks or bonds) p_t, and $I_{j,t}$ is the number of active traders.

An additional differentiating factor, and an extension of the LSV model, is the addition of distinct variables to measure buy herding and sell herding. This buy-herding measure (BHM) and sell-herding measure (SHM) is an addition from (Wermers, 1999) defined as:

$$BHM_{i,t} = HM_{i,t}|p_{i,t} > E[p_{i,t}]$$
$$SHM_{i,t} = HM_{i,t}|p_{i,t} < E[p_{i,t}]$$

In case $p_{i,t} = E[p_{i,t}]$, neither BHM nor SHM is calculated for that security-quarter. Otherwise, by definition, every security-quarter has a BHM or an SHM, however, never both. If there is indeed herding by funds in their trading decisions, the average value of one of the herding measures should be significantly larger than their counterpart.

Following the literature, any security with less than five active traders in a given quarter is not included in the analysis (Lakonishok et al., 1992; Wermers, 1999). Active traders are defined to be individual portfolios that trade a given security during a given period of time, for the purposes of this paper said period of time is defined as a quarter. Four different activity thresholds are calculated, a minimum of 5 trades per security-quarter, 10 trades per security quarter, 20 trades per security quarter, and 30 trades per security-quarter. For each threshold, each herding measure is once again calculated adjusting for the restriction in sample.

CHAPTER 5 Results

5.1 Overall Levels of Herding

The levels of institutional herding in the various securities are displayed in Tables 2 and 3. It is clear from the initial analysis of the results that for both stocks and bonds there are clear signs of herding by institutional investors for all securities with at least 5 trades per quarter. Interestingly, there are similar patterns displayed for both stocks and bonds. For all thresholds, there are more observed security-quarters displaying buy-herding than there is sell-herding. Contrastingly, in the lower thresholds of activity, sell-herding is stronger for bonds than its buy-herding counterpart, and overall herding levels are stronger for bonds than they appear to be for stocks.

Table 2: Herding measures (in percent) of stock investors

Trades	Category	Mean	Std. Error	Std. Dev.	Stock-Quarters
≥ 5	HM	10.85%***	0.000 02	0.103 52	27,693,974
	BHM	12.78%***	0.000 03	0.114 26	15,993,407
	SHM	8.22%***	0.000 02	0.079 45	11,684,425
	BHM-SHM	4.56%***	0.000 04		
≥ 10	HM	10.07%***	0.000 02	0.094 69	25,673,881
	BHM	11.81%***	0.000 03	0.105 88	14,517,801
	SHM	7.81%***	0.000 02	0.071 72	11,145,976
	BHM-SHM	3.99%***	0.000 04		
≥ 20	HM	8.92%***	0.000 02	0.081 41	22,167,580
	BHM	10.39%***	0.000 03	0.093 79	12,065,124
	SHM	7.17%***	0.000 02	0.058 93	10,098,459
	BHM-SHM	3.22%***	0.000 03		
≥ 30	HM	8.28%***	0.000 02	0.075 00	19,242,054
	BHM	9.50%***	0.000 03	0.087 88	10,047,725
	SHM	6.94%***	0.000 02	0.054 67	9,192,350
	BHM-SHM	2.56%***	0.000 03		

Note: * , p-value < 10% ; **, p-value < 5% ; *** , p-value < 1%.

5.2 Stock Herding

Looking specifically at stocks, herding levels at the lowest threshold of activity (5 or more trades) amount to around 10.85%. Intuitively, this represents the fact that if a security were traded by 100 funds during a given quarter, close to 11 more institutions trade on the same side of the market than would be expected under the hypothesis that funds make independent decisions of one another. It is interesting to see that, at the lowest threshold of activity, the highest level of herding can be seen at 12.78%. Sell-herding at the same activity level is 8.22%, indicating that there is also sell-herding present, at a lower intensity than that evidenced in the buy-side of the market. The expectation would be that the difference between the buy-side and the sell-side of the market would be null, given that every trade requires a buyer and a seller. However, when looking at the difference in averages between buy-herding and sell-herding it can be seen that buy-herding is significantly higher than sell-herding, by a margin of around 4.56%.

Looking at all activity thresholds a trend becomes apparent, the more a security is traded per quarter, the lower the level of herding. This applies to both buy- and sell-herding which also decrease as trading activity increases. The difference between buy-herding and sell-herding also decreases as the threshold increases, however, buy-herding is consistently and significantly higher than sell-herding irrespective of threshold. This is consistent with previous findings for herding in stocks in the American market (Wermers, 1999).

Having a more detailed look at the intermediate activity thresholds, in spite of the overall decline in overall herding, the levels of buy-herding remain north of ten percent. Following the previously mentioned intuition, this indicates that were there 100 investors, it could be seen that there are ten or more investors that are buyers above what would be expected. In terms of marginal outlook, it can be seen that there remains a significant difference between buy and sell herding

The results on the levels of herding presented in this paper are robust irrespective of the activity level chosen. It is clear that herding in stock markets is driven mainly by buy-side herding for the analysed period in our sample.

Table 3: Herding measures (in percent) of bond investors

Trades	**Category**	**Mean**	**Std. Error**	**Std. Dev.**	**Bond-Quarters**
≥ 5	HM	24.34%***	0.000 05	0.189 39	12,192,565
	BHM	19.59%***	0.000 05	0.136 54	6,326,648
	SHM	29.47%***	0.000 09	0.222 21	5,865,806
	BHM-SHM	−9.88%***	0.000 10		
≥ 10	HM	22.61%***	0.000 06	0.172 41	7,328,360
	BHM	20.38%***	0.000 07	0.137 45	4,121,217
	SHM	25.47%***	0.000 11	0.205 39	3,207,143
	BHM-SHM	−5.09%***	0.000 13		
≥ 20	HM	22.54%***	0.000 09	0.162 00	3,017,404
	BHM	22.62%***	0.000 10	0.141 90	1,892,645
	SHM	22.39%***	0.000 18	0.191 10	1,124,759
	BHM-SHM	0.24%***	0.000 19		
≥ 30	HM	24.57%***	0.000 13	0.156 85	1,526,342
	BHM	25.80%***	0.000 14	0.142 07	1,046,959
	SHM	21.86%***	0.000 26	0.182 16	479,383
	BHM-SHM	3.94%***	0.000 27		

Note: * , p-value < 10% ; **, p-value < 5% ; *** , p-value < 1%.

5.3 Bond Herding

The trends presented in stocks do not seem to be replicated for bonds. Overall herding patterns are higher at all activity thresholds, with herding levels of 24.34%, 22.61%, 22.54%, and 24.57% at their respective activity thresholds. It is of note to observe that none of the highest level of overall herding is seen at the highest activity threshold, contrary to the herding observed in stocks. There is an interesting pattern when observing overall herding per activity threshold as the highest levels appear at the lowest and highest thresholds. The intermediate levels of herding (10 and 20 minimum trades per quarter) see a small decline in overall herding.

The driver of herding for bonds is also noticeably distinct from that seen in stocks. When looking at the lowest activity threshold, there is a large and significant difference between buy- and sell-herding, with sell-herding being close to ten percent higher. More specifically sell-herding at the lowest activity threshold sits at close to 30%, which implies that if 100 institutions trade a given bond during a given quarter, close to 30 of them trade more on the sell-side of the market than would be expected were they making decisions independently of one another. This is consistent with previous results that also find that at varying levels of activity, sell-herding seems to be the driver of overall market herding (Cai et al., 2019). A similar pattern appears at the next activity threshold where overall herding is slightly smaller than that present at the lowest activity threshold, with overall herding sitting at around 22.61%. The level of sell-herding remains higher than buy-herding, however, the difference is smaller as it goes from around 9.88% to around 5.09%, representing a notable decrease in herding skew in the market. The difference, though smaller in magnitude, remains significant. Sell-herding at the second activity threshold sits at around 25.47%, indicating a significant level of herding on the sell side of the market.

Where the data presents a break from that seen in previous literature, is when looking at the higher two activity thresholds there is a reversal in the driver of herding. At the minimum activity threshold of twenty trades per quarter, buy- and sell-herding are as close to even as seen in either the analysis of bonds or stocks, irrespective of activity level. Overall herding at this activity threshold sits at around 22.54%, less than the level seen at the lowest activity threshold but quite similar to the previous activity threshold. Interestingly, this is the first activity level at which buy-herding becomes the main driver of overall herding, by a statistically significant margin of 0.24%. At the highest activity threshold there is an infatuation of the reversal presented at previous activity levels, as buy-side herding goes from being close to even with sell-side herding to presenting a margin of around 3.94% in favour. Of note is that the overall level of herding ticks back up at the highest activity threshold to a level higher than that presented at any other activity threshold.

Similar to the case of stocks, the level of sell-herding diminishes as the activity threshold increases. This presents a contrasting position relative to the literature as previous findings show that sell-herding tends to decrease as the activity threshold is increased, however, this refers to results relating to stock market herding. The literature on bonds suggests that sell herding should increase as the number of trades increases (Cai et al., 2019; Wermers, 1999), however, this paper's findings regarding bond sell-herding are in alignment with stock market sell-herding instead.

CHAPTER 6 Conclusion & Discussion

6.1 Discussion

This paper lies at the intersection of much of the existing literature around herding. Said intersectionality is further emphasized by this paper's presentation of multiple types of securities by the same subset of funds. The single subset of funds, along with the study of both stocks and bonds, is the differentiating feature of this paper compared to its peers. It, however, falls short of the top tier of papers on the subject as it does not tackle the impact of the presented herding on asset prices or abnormal returns.

Regarding the results presented in this paper, they exist in both alignment and juxtaposition of previous results found in the literature. In the realm of stock market herding, the results tend to align with those in the broader literature, particularly displaying patterns similar to those described by Wermers (1999). The trends described fall well within the expectations described in the literature, with a progressive decline in herding as the number of trades per stock-quarter increases. Where the juxtaposition is presented is when looking at herding results around bonds

6.2 Limitations

One of the fundamental challenges of the study of herd behaviour is the conciliation of the existing theoretical frameworks explaining the underlying mechanisms upon which the phenomenon is explained, with the phenomenological understanding of herding. There is yet to be presented a mechanism through which these two ends of the literature on herding can be brought together. A rather large impediment in this conciliation process is the inability of researchers to accurately analyse the thought process of investors, only being able to hypothesize a given investors reasoning based on the observed decisions they make and the outcome of said decisions. It is, fundamentally, an issue of data availability, which makes it both possible to solve in theory but practically extremely unlikely.

This paper also evidences clear limitations, particularly relating to the author's ability to process the portfolio holdings dataset, which is composed of over 200,000,000 entries. The size of the dataset, and the practical limitations of performing computations on such a large dataset, resulted in the sample being limited to the funds for which there was data at both the starting point of the sampling period, Q1 2004, and the end sampling period, Q4 2019. This may introduce survivorship bias to the analysis, making it such that the findings remain conditional to the setting presented in this paper and cannot immediately be extrapolated as to represent the entirety of the U.S. market much less other international security markets.

6.3 Conclusion

In this paper, the prevalence of herding across securities was analysed. Previous research has shown that herding seems to be a prevalent phenomenon in markets, however, the magnitude and direction of it has been the subject of much discussion. It is the subject of little debate whether the phenomenon of herding exists and whether it is evidenced across capital markets (Deng et al., 2018), where it has been hypothesised to be one of the key drivers behind market instability and volatility (Komalasari et al., 2022). As to quote (Welch, 2000): “Herding in financial markets, in particular, is often presumed to be pervasive, even though the extant empirical evidence is surprisingly sparse”. Though the quote may not be recent, the sentiment remains prevalent amongst academics interested in the study of herding in financial markets. Most of the research, however, has been focused on herding in stock markets, with limited research into other securities in spite of the hypothesised prevalenced of the phenomenon. Therefore, the aim was for this paper was to provide a consolidated look at herding across asset classes. The hope has been to answer the question: “is institutional herd behaviour a present phenomenon in financial markets, and what is the nature of herding across asset classes?”

To answer the research question posed by this paper, the quarterly holdings of institutional funds were analysed for a period of 15 years between Q1 2004 and Q4 2019. Based on the reported holdings, herding measurements are taken following the methodology established by (Lakonishok et al., 1992). The specifications introduced by (Wermers, 1999) are added to analyse the levels of herding while allowing for the differentiation between patterns seen in the buy-side and the sell-side of the market. The results show that herding, irrespective of activity level, is present in security markets with very distinct presentations depending on the security in question and the activity threshold analysed.

This paper, therefore, concludes by reaffirming the prevalence of herding across security markets. Further aligning with the research in finding the diminishing presence of herding in stocks as the required number of trades is increased. However, not all findings lie in alignment with the literature, in particular not in the case of bonds. This paper’s findings lie partially in contradiction of previous findings, as sell-herding was not found to increase for bonds as the activity threshold was increased. The opposite held true, with sell-herding decreasing and buy-herding increasing.

In conclusion, herding seems to be ever-present in security markets. However, a lot of research remains to be done regarding the impact of herding on the market as a whole, as well as its impact on individual assets and portfolios. More importantly, there is yet to be found empirical substantiation for the theoretical underpinnings that have, unfruitfully, to explain the mechanisms through which the phenomenon of herding comes to occur. This paper has abstained from arguing in favour of, or against, any of the theories presented to explain herd behaviour, but has presented evidence that suggests that there is no ‘one size fits all’ presentation of herding.

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APPENDIX A Figures

Figure 1: Herding hierarchies (Hirshleifer & Hong Teoh, 2003)

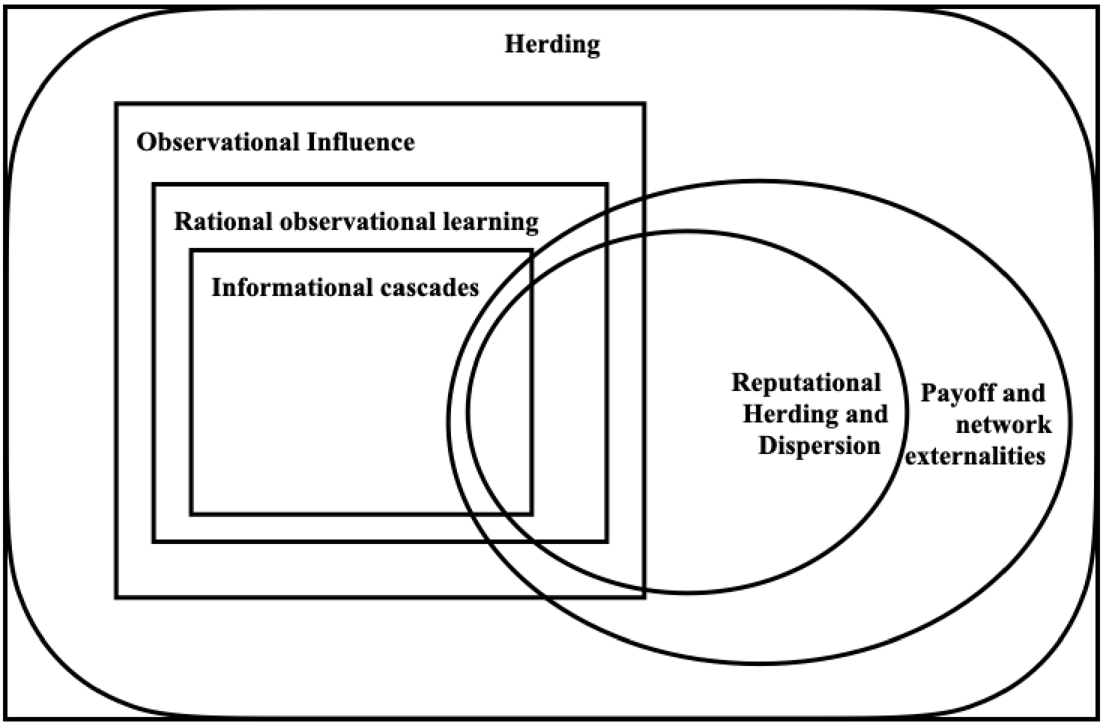


Figure 2: Number of unique investors per quarter

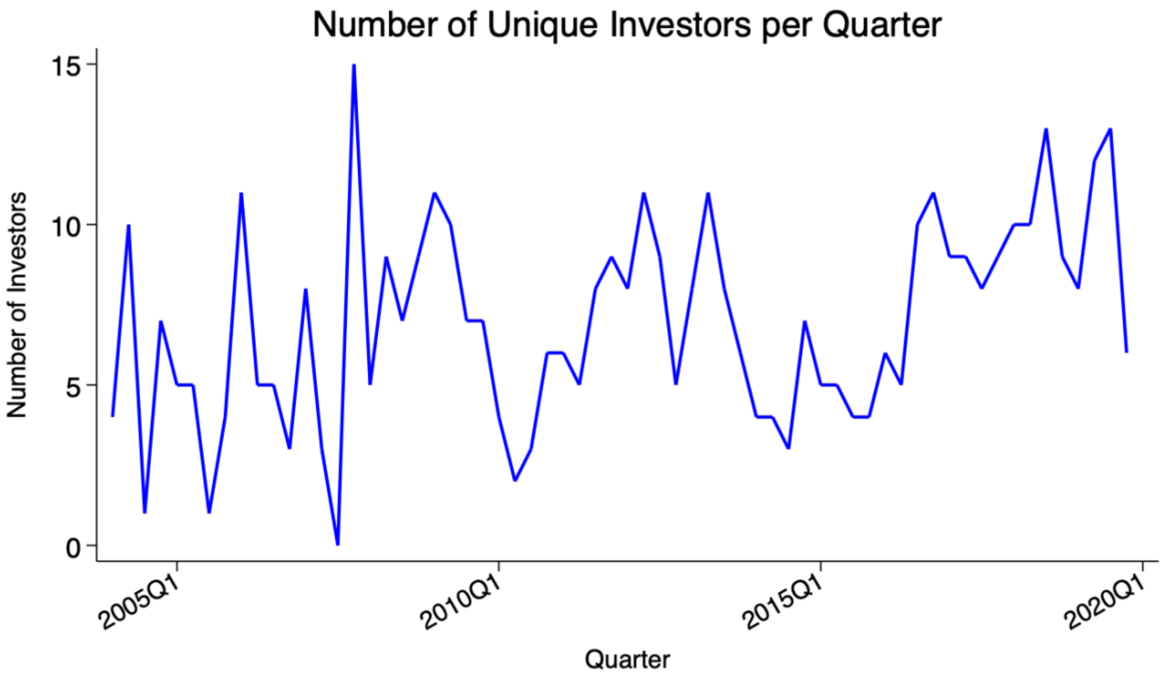
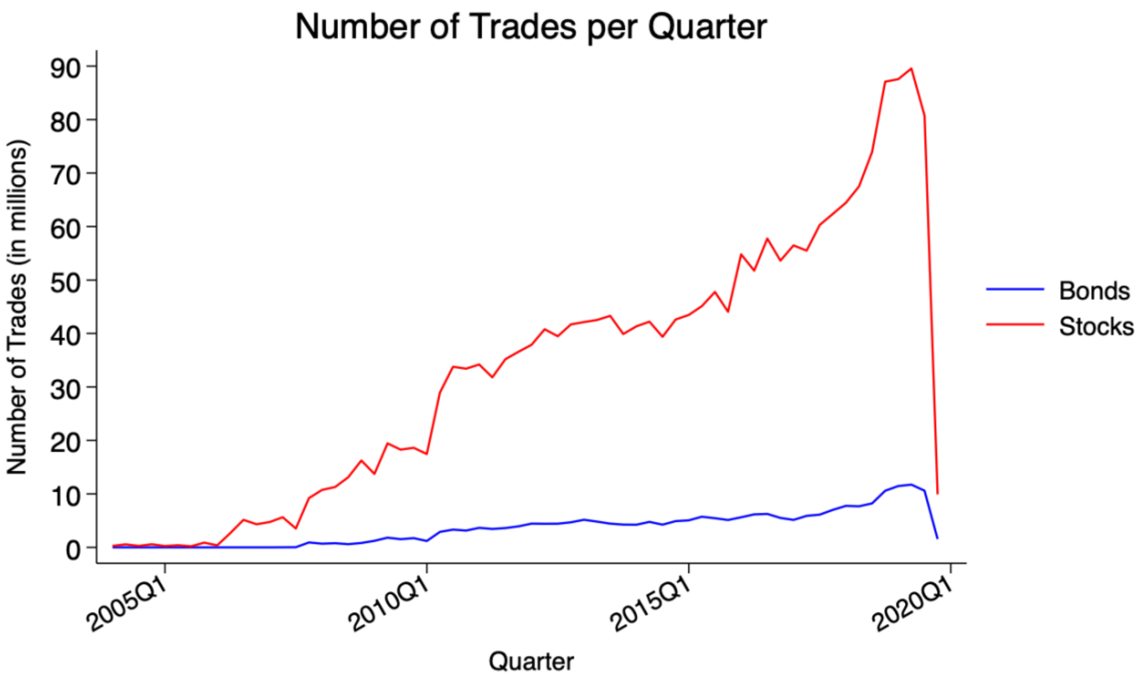


Figure 3: Number of trades per quarter (in millions)



APPENDIX B Tables

Table 1: Average investor profile, transactions per quarter (rounded to the nearest integer)

Security	Transactions	Purchases	Sales
Stocks	79	54	25
Bonds	56	28	28

Table 2: Herding measures (in percent) of stock investors

Trades	Category	Mean	Std. Error	Std. Dev.	Stock-Quarters
≥ 5	HM	10.85%***	0.000 02	0.103 52	27,693,974
	BHM	12.78%***	0.000 03	0.114 26	15,993,407
	SHM	8.22%***	0.000 02	0.079 45	11,684,425
	BHM-SHM	4.56%***	0.000 04		
≥ 10	HM	10.07%***	0.000 02	0.094 69	25,673,881
	BHM	11.81%***	0.000 03	0.105 88	14,517,801
	SHM	7.81%***	0.000 02	0.071 72	11,145,976
	BHM-SHM	3.99%***	0.000 04		
≥ 20	HM	8.92%***	0.000 02	0.081 41	22,167,580
	BHM	10.39%***	0.000 03	0.093 79	12,065,124
	SHM	7.17%***	0.000 02	0.058 93	10,098,459
	BHM-SHM	3.22%***	0.000 03		
≥ 30	HM	8.28%***	0.000 02	0.075 00	19,242,054
	BHM	9.50%***	0.000 03	0.087 88	10,047,725
	SHM	6.94%***	0.000 02	0.054 67	9,192,350
	BHM-SHM	2.56%***	0.000 03		

Note: * , p-value < 10% ; **, p-value < 5% ; *** , p-value < 1%.

Table 3: Herding measures (in percent) of bond investors

Trades	Category	Mean	Std. Error	Std. Dev.	Bond-Quarters
≥ 5	HM	24.34%***	0.000 05	0.189 39	12,192,565
	BHM	19.59%***	0.000 05	0.136 54	6,326,648
	SHM	29.47%***	0.000 09	0.222 21	5,865,806
	BHM-SHM	−9.88%***	0.000 10		
≥ 10	HM	22.61%***	0.000 06	0.172 41	7,328,360
	BHM	20.38%***	0.000 07	0.137 45	4,121,217
	SHM	25.47%***	0.000 11	0.205 39	3,207,143
	BHM-SHM	−5.09%***	0.000 13		
≥ 20	HM	22.54%***	0.000 09	0.162 00	3,017,404
	BHM	22.62%***	0.000 10	0.141 90	1,892,645
	SHM	22.39%***	0.000 18	0.191 10	1,124,759
	BHM-SHM	0.24%***	0.000 19		
≥ 30	HM	24.57%***	0.000 13	0.156 85	1,526,342
	BHM	25.80%***	0.000 14	0.142 07	1,046,959
	SHM	21.86%***	0.000 26	0.182 16	479,383
	BHM-SHM	3.94%***	0.000 27		

Note: * , p-value < 10% ; **, p-value < 5% ; *** , p-value < 1%.