Exploring Short-Term Herding Behavior in the US Corporate Bond Market

AIKATERINI-MARIA G. KATSAROU

Thesis submitted to the

Department of Accounting & Finance

of the Athens University of Economics and Business

as partial fulfillment of the requirement for the

Master's Degree

Athens

December, 2017

We approve the Thesis of

AIKATERINI-MARIA KATSAROU

[ACADEMIC SUPERVISOR]	**[SIGNATURE]**
GEORGE CHALAMNDARIS	....
[CO EXAMINER]	**[SIGNATURE]**
ANDRIANOS TSEKREKOS	....
[CO EXAMINER]	**[SIGNATURE]**
LEONIDAS ROMPOLIS	....

[21/12/2017]

CERTIFICATION OF THESIS PREPARATION

"I hereby declare that this particular thesis has been written by me, in order to obtain the Postgraduate Degree in Accounting and Finance, and has not been submitted to or approved by any other postgraduate or undergraduate program in Greece or abroad. This thesis presents my personal views on the subject. All the sources I have used for the preparation of this particular thesis are mentioned explicitly with references being made either to their authors, or the URL's (if found on the internet)."

[FIRST AND LAST NAME]	[SIGNATURE]
AIKATERINI-MARIA KATSAROU	....

Acknowledgments

I would like to express my sincere gratitude to my supervisor, Assistant Professor George Chalamandaris, for his support and his guidance throughout my M.S. program. His valuable input and constructive suggestions offered a great help to my master thesis.

I would also like to acknowledge my colleague Erjona Simja for her wonderful collaboration. I am gratefully indebted her for her valuable comments and her suggestions through the process of researching and writing of this master thesis.

Table of Contents

Introduction

In this dissertation we investigate herding behavior in the U.S. corporate bond market. The notion of herding behavior has been the subject to several fields of social sciences as zoology, psychology, neurology and sociology. Moreover, this phenomenon has been particularly studied by behavioral finance. Essentially, in economics and finance herding is defined as the tendency of investors to mimic actions of other investors into or out of the same securities.

Several studies have dealt with investors' herding behavior in stock exchange market. The majority of them have reported a very low (if not at all) level of herding in the particular market. Equity markets are very popular, since they have attracted interest of media, researchers and investors (retail and institutional). Thus, they have reached pretty high level of automatization, transparency, liquidity and a working efficiency in general, at least for small and thin margin trades. In this regard, the reported levels of herding behavior in the particular market make sense.

On the other hand, US corporate bond market recently started attracting the attention of investors. Characteristically, the net increase on corporate bond issuances by nonfinancial firms averaged $300bn between 2007 and 2016. This shift of investors' portfolios was mainly attributed to the zero interest policies that Federal Reserves imposed for almost a decade. In addition, corporate bond market is an inherently opaque market with intensive liquidity issues. In an attempt to increase transparency in the market the Financial Industry Regulatory Authority (FINRA), introduced on July 1st, 2002 a platform known as the Trade Reporting and Compliance Engine (TRACE). Specifically, TRACE is electronic platform on which all participants in the over the counter (OTC) market of US corporate bonds are obliged to report their trades. Despite the fact that this regulation succeeded to usher more retail investors in the market and thus in turn to increase the market liquidity, institutional investors were opposed. In particular, institutional investors raise concerns that the instant dissembling of their trades might give advantage to other investors handling them, as well as their private information would be revealed. They also alleged that large trades would be impeded and ultimately the long term liquidity of the market would be harmed.

Against this backdrop, US corporate bond market constitutes an ideal pool of observations to be used in the study of investors' herding behavior. In this regard, we are taking advantage of a comprehensive dataset from TRACE to examine whether the participants of US corporate bond market do herd. In doing so, we address three key empirical questions in this dissertation: Do investors herd in the corporate bond market? If so, which investors' category exhibits herding behavior on their daily trading activity? Last but not least, which are the main determinants of such behavior? In particular, we conduct a thorough analysis to recognize micro-structure patterns in corporate bond market. Due to the fact that our data is reported on a daily basis, we cannot talk firmly about herding behavior. However, we can employ the methods suggested by previous studies (i.e. LSV and Sias approach) to estimate the magnitude of herding.

Our main results are as follows,

- We document the existence of herding behavior in US corporate bond market.
- Retail investors exhibit a more severe level of herding than institutional investors.
- We reveal the inefficiency of corporate bond market to cover the demand even of retail investor in short term period, creating patterns in their daily demand.
- Institutional investors do not differentiate their behavior among bonds of different credit rating status and liquidity level, whereas it seems to herd more on bonds with remaining maturity between five to fifteen years as well as on bonds issued by Financial Institutions.
- Retail investors herd intensively on more uncertain issues. This behavior is expressed by higher level of herding on lower credit rated and longer maturity bonds as well as on bonds issued by Financial Institutions.
- Lastly, both Institutional and Retail investors expand their herding behavior on issuer level. Interestingly, retail investors exhibit the same level of herding on issuer and individual bond level.

The rest of this dissertation is organized as follows. Chapter 2 presents the main theories associated with herding behavior. Chapter 3 reviews previous works related to this dissertation. Chapter 4 describes the examined market, the employed data as well as our construction of herding measures and the methodology used. Chapter 5 presents and analyzes the results of this current study. Lastly, Chapter 6 summarizes conclusions of our research. We also provide an Appendix which contains an attachment of results using LSV approach.

Theories of Herding

Many theories have been proposed across the literature to explain institutional herding. The assumption of asymmetric information suggests that expenditures (time and financial costs) of gathering information make herding prudent and even reasonable for the market participants, who assume that crowd knows more than they do individually and therefore base their decisions on the actions of the majority. Under this case, individual investors are expected to expose themselves, at a greater extent, to the tendency that herd generates in relation to institutional investors, since the latter have access to better information and superior methods for finding this information, thus reducing their need to emulate their hypothetically better-informed colleagues. The psychological prejudices such as compliance can reinforce the existing one anger behavior among individuals.

An alternative approach that differs from the above stipulates that herding behavior is likely to be more prevalent among institutional, such as mutual funds, rather than between individual investors. The positions of institutional investors, because they are mandatory under the law, are more readily perceived by their colleagues in the room and hence there is a greater tendency to imitate between these categories of investors. Since the individual-individual investors are not forced to disclose their investment positions, such as institutional ones, it is more difficult for individuals to observe the structure and the portfolio moves of the remaining private investors.

The second hypothesis is that some institutional investors such as fund managers are evaluated based on their performance over other capital administrators. In this case it is preferable to keep up even mistakenly with the rest of the institutional-like herd, rather than walking and to take individually wrong investment decisions.

There is a rich theoretical literature suggesting both rational and irrational explanations for herding by investors. According to Bikhchandani & Sharma, (2001) the behavior of the herd is divided into “spurious” (unintentional) herding, where investors face similar fundamental-driven information and therefore make identical decisions, and “intentional” (rational) herding, where investors have an intention to mimic the behavior of others. The former may lead to an efficient outcome whereas the latter might be inefficient. Not only is intentional herding characterized by fragility and idiosyncrasy, but also it can lead to excess volatility, systemic risk, and fragile markets.

The rational model focuses on externalities (profit and maximizing utility), when the decision process is distorted by difficulties in finding information. As far as the behavioral aspect model is concerned, this asserts that decision makers to save costs from processing and acquisition information (using their rationality and heuristic rules) might be bound by endogenous and exogenous constraints, including the investor's psychology.

There are several potential reasons for rational herding behavior in financial markets. Among the most important of these are investigative herding, information cascades, concern for reputation, and compensation structures.

Investigative herding arises when there is a positive cross-section correlation between institutional investors' information, i.e. institutional investors follow the same signals. Froot , et al., (1992) assert that if speculators have short horizons, they may herd trying to learn information that other investors know. More specifically, their model shows the existence of short-term speculators, which in turn implies an informational inefficiency. Although at the pricing stage the market may be efficient, and investors may tend to concentrate on one set of information due to poor quality or are irrelevant to fundamentals. Their results can be interpreted by positive informational spillovers. As an increasing number of speculators obtain a given piece of information, it will be disseminated in the market and therefore it is profitable to acquire this set of information at an early stage. Under this case, herding equilibria may occur in the sense that traders may focus on different variables at different times.

Furthermore, institutions might infer information from each other's trade and hence follow the crowd disregarding their own private information. This phenomenon is referred to as information cascades and can explain how such social conventions and norms occur, are maintained, or change over time. For example, the fact that investors enter the market at a later stage might be rational since they mimic the trading behavior of previous investors (that may be of possess private information) ignoring their own private information. As far as their consequences are concerned, informational cascades might have an impact over perfectly rational individuals and lead to the creation of bubbles.

Banerjee (1992) analyzes a decision model where it is rational for decision makers to look at the decisions made by previous decision makers since the latter may possess related information. He shows that the decision rules that are adopted by optimizing individuals might be characterized by herding behavior; i.e., people will be doing what others are doing rather than employing their information.

Bikhchandani, et al., 1992 discuss a general sequential choice model where a decision maker will act only on the information acquired from previous decisions disregarding private information (as will latter decision makers). They assert that, irrespective of the social desirability of the outcome, the reasoning might be entirely rational. Not only can informational cascades explain conformity, but also, they interpret the rapid spread of new behaviors. Lastly, they argue that conformist behaviors may be fragile and idiosyncratic because informational cascades rely on even a small set of information.

Avery & Zemsky, (1998) study the relationship between asset prices and herd behavior, which arises when traders follow the trend in past trade. They show that the existence of herding in the terms of an informational cascade is not possible, if both simple information structures and price mechanism are assumed. More complicated information structures, however, can lead to herd behavior and it might affect asset prices only when the market is uncertain for both and the information of the average trader and the asset value. Lastly, a sufficiently complex information structure makes price bubbles possible.

To study herding behavior in financial markets, Cipriani & Guarino, (2005) show that in a frictionless laboratory market in which subjects are trading for informational reasons, herding behavior rarely arises. The results of this laboratory experiment are in line with the theoretical predictions of Avery & Zemsky, (1998). Theoretical evidence, however, do not entirely capture the behavior observed in the laboratory financial market. In some cases, there are informed traders that follow a contrarian strategy or choose to disregard their own private information and abstain from trading.

Scharfstein & Stein, (1990) approach herding behavior with another methodology based on the reputational concerns of fund analysts or managers. Reputation or, more broadly, career concerns arise in the face of uncertainty about the ability of a manager. The main idea is that if an investment manager and her employer are uncertain of the manager's ability to pick the right stocks, conformity with other investment professionals preserves the uncertainty concerning the ability of the manager to manage the portfolio. Moreover, the "sharing-the-blame" effect based on correlated prediction errors and reputation concerns in labor markets may lead managers to follow each other's decisions, disregarding their own private information. Their learning model presents the labor market as competent to update its understanding of the manager's competency from the investment decisions a manager is making. In this way, manager concern for labor market reputation may lead to rational and irrational herding behavior (institutional managers trade in the same direction as others because they do not want to risk their reputation by acting differently from the crowd). To state differently, herding might be considered as insurance that the manager will not under perform his collegues. (Rajan, 2006).

Trueman's theoretical model (1994) indicates that the perception of analyst abilities affects analyst compensation. There is an assumption that the earnings forecasts of analysts do not necessarily reflect in an unbiased manner their private information, but they tend to announce forecasts closer to prior earnings expectations. It is also essential to note that analysts tend to forecast earnings like those previously released by other analysts in an attempt to imitate higher ability and acquire higher compensation.

Graham, (1999) argues that analysts are more likely to herd when they are characterized by high reputation or low, or when there is strong public information inconsistent with analyst private information. Herding behavior can also arise when private information signals across analysts present positive correlation. To test his model, he utilizes a dynamic measure of reputation that is constructed with data from analysts who publish investment newsletters.

According to Keynes, (1936) investors are affected by sociological factors (e.g. social conventions) that may drive market participants to mimic the actions of others during periods of uncertainty. Moreover, Baddeley et al (2004) point out that even adepts may resort to imitation behavior, given information deficiency, asymmetry, and the employment of common heuristic rules. Therefore, irrational herd behavior can occur as the consequence of psychological stimuli and constraints, such as psychological biases and pressure from social circles and/or social conventions.

Shleifer & Summers, (1990) divide investors into two main categories, arbitragers, and noise/liquidity traders. Arbitrageurs or called "rational speculators" form fully rational expectations about security returns, whereas noise/liquidity traders (Black; 1986) act irrationally on noise and whose trading behavior may be bound by systematic biases. Moreover, they point out that some shifts in investor expectations for assets or shifts in investor sentiment appear to be irrational and not justified by fundamentals (e.g. investors' response to pseudo-signals such as advice by "financial gurus".

Furthermore, irrational, or behavioral herding behavior contains all the errors the investor does, whether they are originated from investor's sentiment or his mental conception. In the face of aversion to their loss or adhesion to reference points, people are likely to invest their money, in a loss-making investment product in the hope that they will soon win the "losers". In doing so, they act myopically either by selfishness and greed or by errors pertained to their perception.

In this sense, lots of economists suggest formal models on how investor sentiment may affect investor trading behavior and lead to systematic asset mispricings. For instance, Barberis , et al., (1998) present a "parsimonious model" of investor sentiment that predicts investor overreaction and/or underweighting to information. Under this interpretation, their model predicts an overreaction to a long string of bad earnings news or sales figures and the underweighting of informative bad news of a different type that arrives afterwards. Lastly, their results are in line with empirical evidence on the shortcomings of personal judgment under uncertainty.

Daniel , et al., (1998) suggest a theory where investors are overconfident with respect to their private information and suffer from biased self-attribution. These biases can lead to asymmetric changes in investor's confidence as a function of investment outcomes. Their findings show that overconfidence might cause long-lag autocorrelations, excess volatility and return predictability.

Hong & Stein , (1999) propose a model with two types of boundedly rational market participants: "newswatchers" and "momentum traders." Each newswatcher constitutes an agent that observes some private information, but fails to obtain other newswatchers' information from prices. In their study, short-run price underreaction is originated from slowly diffusing information concening future fundamentals. That slow information dissemination is exploited by momentum traders which, in turn, leads to long-term overreaction.

Literature Review

In one of the earliest studies Lakonishok, et al., (1992; LSV henceforth) utilize 769 US tax-exempt equity funds' (mostly pension funds) quarterly ownership of shares data from 1985 through 1989. By design, the LSV measure gauges whether a disproportionate number of institutions are buying (selling) a certain security beyond the market-wide buying (selling) intensity in each period (it will be described in thoroughly in the Appendix). They distinguish the trading of these money managers between herding and positive-feedback trading. Interestingly, LSV conclude that institutional money managers do not destabilize prices of individual stocks, i.e. economically non-significant levels of herding, while simultaneously they prove less herding in the small stocks and technology stocks with uncertain cash flows. They also find weak evidence of imitation behavior at the industry level than in individual stocks. Finally, their paper plays a profound role for later studies as it introduced the fundamental herding measure.

Grinblatt, et al., (1995; henceforth GTW) employing the quarterly ownership data on portfolio changes of 274 mutual funds for the period 1974 and 1984 find similar levels of herding as found by LSV (1992). This study examines the extent to which mutual funds purchase stocks based on their past returns and at the same time why they tend to display herd behavior. As far as momentum trading is concerned, GTW find strong evidence that herding can arise by investors in buying stocks that were past winners than investors selling past losers. In this sense, herding that arises on the sell side, although positive, seems to be unrelated to past returns. In contrary with LSV approach they differentiate funds according to their investment purpose to examine for significant heterogeneity in the mutual funds. Specifically, GTW divide mutual funds into balanced funds, aggressive growth funds, growth funds, growth-income funds as well as income funds. Their findings are in line with that herding being even weak after examining for objectives.

A different methodology is proposed by Christie & Huang, (1995; CH henceforth), who suggest a metric that measures investor herding towards the market consensus. Daily and monthly returns from 1962 to 1988 are used to measure the cross-sectional standard deviation of returns, or dispersions. They point out that during extreme market movements investors might suppress their own beliefs and base their investment decisions solely on the market consensus. Consequently, individual returns will not have repelled too far from the market return and thus return dispersions should be relatively low. Lastly, when stocks sensitivity towards the market differs from rational asset pricing suggests that dispersions may increase.

Wermers , (1999) performed the most comprehensive study to date utilizing quarterly holdings data for all mutual funds in existence between 1975 and 1994. Using the LSV measure of herding, he finds little herding in trades by the funds taking place in an average stock. Furthermore, he shows high level of herding in small stocks. However, small stocks are not considered typically the preferred holdings of mutual funds. Wermers also finds higher levels of herding in growth-oriented funds than income-oriented funds, which he attributes to positive-feedback trading strategies. Contrary to GTW (1995), he finds greater extent of herding on the sell side than on buy side. Specifically, herding on the buy-side is more prevalent in high past-return stocks, whereas herding on the sell-side is likely to occur in low past-return stocks and simultaneously is unrelated to window-dressing strategies.

By examining the difference between contemporaneous returns and future stock returns, i.e. returns after 6 months on the stock bought by the herds relative to the stocks sold by the herd, he concludes that herding consists a rational choice and simultaneously can contribute bring about incorporation of news into securities prices. This last finding, which played a profound role in his study, is also in line with the fact that continuing price trends could also mean that, as institutional investors herd even more, they drive the prices away from fundamentals. Only if the trends in the prices continue in the subsequent longer period, unattended by herding, can we close with his claim.

In the same spirit with CH, Chang et al. (2000, CCK henceforth) examine the investment behavior on the part of market participants within different international markets. They propose a test of herding behavior to capture any possible non-linearity between market return and the asset return dispersions. Their findings indicate the absence of herding in the US and Hong Kong, partial herding in Japan, and presence of herding for South Korea and Taiwan. Moreover, CCK find that for the markets which exhibit herding there is information associated with macroeconomic fundamentals (rather than information at the firm level) that affects investor behavior.

Sias, (2004) employing the total number of institutional investors required to file 13F reports from 1983 through 1997 examines the existence of institutional herd behavior. Taking a new approach, he shows that institutional demand in each quarter can be associated with either herding in others' trades or herding in their own past trades. His findings are consistent with the fact that institutions accumulate and liquidate positions over time to reduce trading costs. Moreover, he suggests that institutions herd because of following information revealed from each other's trades and that, as trading by institutional investors is strongly related to contemporaneous returns. In other words, institutional herding is initially correlated with the manner information diffuses, as the positive relation between contemporaneous returns and trading by institutional investors originates from the information contained in their activities.

Choi & Sias, (2009) using quarterly data from 1983 through 2005 examine the existence of institutional industry herding in U.S. market. Their strong empirical findings reveal that the institutional investors follow each other into and out of the same industries. They show that the fraction of institutional traders buying an industry the previous quarter is correlated with the fraction buying this quarter. Consistent with reputational herding, they find that institutional industry herding can arise from managers' decisions rather than underlying investors' flows. It is also unrelated to institutional industry momentum trading and simultaneously is more prevailing in smaller and more volatile industries. Lastly, herding might lead industry market values away from fundamentals.

Cai, et al., (2016) utilize a dataset of quarterly U.S. corporate bond holdings for insurance companies, mutual and pension funds from 1998 to 2014. Adopting LSV herding measure examine the extent of herding by institutional investors in the U.S. corporate bond market. They conclude that institutional herding is significantly greater in corporate bonds than equities and especially on the sell side, driven by imitation behavior. Applying the methodological approach of Sias, they show that bond trading is correlated with the fact that investors follow others' trade. They also find that buy herding is related to permanent price adjustments, whereas herding on sell side arises in transitory yet significant price deteriorations and thus excess price volatility.

Other studies examine institutional investor herding in non-U.S. markets and their findings indicate that in smaller markets herding may be more prevalent.

Iihara, et al., (2001) examine the yearly change in ownership and stock returns using aggregate data during the period of 1975 to 1996 as a proxy for investor herding in Japan. In addition to institutional and individual investors, they analyze the behavior of foreign investors because foreign investors might not follow similar trading activity to Japanese investors. Specifically, they conclude that institutional and foreign investors' herding is more prevalent than individual investors' herding, as both foreign and institutional investors impact more stock prices. Their findings are also consistent with intra-year positive feedback trading by both foreign and institutional investors.

Caparrelli , et al., (2004) using data for the period of 1988-2001 evaluate herding effects in the capital markets and specifically in the Italian Stock Exchange. Consistent with Christie and Huang (1995), they show that herding may occur in extreme market conditions, i.e. during periods of great stock levels and sustained growth rate. Furthermore, their findings show that herding is lower for small-cap companies than for large-caps, and tends to decrease constantly.

Gleason et al. (2004) performed a study to examine the presence of herding in Exchange Traded Funds (ETFs) during periods of market stress. In this way, they use intraday data on nine sector ETFs traded on the American Stock Exchange for the period 1999 to 2002. Employing two differential measures of dispersion, they analyze up and down markets in aggregate and find no evidence of herding by ETF investors. Their results are consistent with the conclusion that, ETF traders trade away from the market consensus during periods of extreme market movements. Moreover, they show that the market reaction to news may not symmetric for up and down markets.

Wylie (2005) employs the herding measure of LSV to test for herding among U.K. mutual fund managers. Specifically, he uses data of the portfolio holdings of 268 U.K. equity mutual funds, taken from semiannual reports to investors over the period 1986 to 1993. He concludes that the herding measure increases in the number of managers trading a stock over a period and is greater only for extreme capitalization individual stocks. In the contrary, little herding is found for other capitalizations or stocks aggregated at the industry level.

Henker et al. (2006) utilize high frequency intraday data on Australian equities for the year 2001-2002 to test market wide and industry sector herding. Not only are their findings considered inconsistent with intraday herding, but also all evidence imply that information is disseminated efficiently among participants in the Australian equity market. Furthermore, their results imply that investors in the Australian equity market have a high level of firm specific information and discriminate between securities as predicted by the rational asset-pricing paradigm.

Walter and Weber (2006) examine the extent to which German mutual fund managers herd in German mutual fund industry (both bull and bear markets). Applying the LSV herding measure and utilizing the trading activity of 60 German mutual funds for the period of 1998 to 2002, they find evidence of herding and positive feedback trading by German mutual fund managers. Specifically, they show that the highest level of buy-side herding may occur during the boom periods, whereas sell-side herding is more prevalent during the crash periods. Interestingly, a significant portion of herding is owing to spurious herding because of changes in benchmark index composition.

Applying the same methodology with CSAD, Economou et al. (2011) test for herding behavior in the Portuguese, Italian, Spanish and Greek market. They construct a survivor-bias-free dataset consisted of daily returns for all stocks listed in these four markets for the period 1998 to 2008. They conclude that during the recent debt crisis of 2007-2008 there is not intense herding behavior in any of the four markets considered.

Holmes et al. (2013) employing the Sias (2004) approach and monthly institutional holdings data for the Portuguese stock market from 1998 through 2005 find clear evidence of herd behavior. By examining institutional herding under different market conditions, they conclude it is intentional rather than spurious. The multivariate analysis suggests that herding is more pronounced when the market declines or market returns are low. In addition, their findings are consistent with the view that reputational reasons and and/or informational cascades may be the cause of the observed behavior.

Galariotis et al. (2015) utilize daily prices for all US and UK constituent stocks from 1989 to 2011 to test herd behavior toward consensus. Adopting CSAD methodological approach, they find the release of macro information is associated with the tendency of US investors to herd toward consensus. Regardless of investment style, the announcement of major macroeconomic information may lead to spurious herd behavior. Moreover, they show that in the US there is herding due to both fundamentals and non-fundamentals during different crises (during the Asian and Russian crisis and during the Subprime respectively). On the contrary, UK investors herd due to due to fundamentals and only during the Dotcom bubble burst.

Our dissertation adds valuable data to existing literature on herding behavior. Contrary to other researches that use the changes on investors' position at the examined issues, we employ directly transaction level data (e.g. trades and traded volumes). Moreover, by taking advantage of a comprehensive dataset from TRACE we examine corporate bond market on short term basis, while the existing studies are focused on longer term examination of equity market. Since our data is reported daily, we cannot firmly talk about herding behavior. However, we can employ the methods suggested by previous studies (i.e. the LSV measure and the Sias approach). In doing so, we conduct an analysis to recognize micro-structure patterns in corporate bond market.

Data and Methodology

Corporate Bond Market Overview

Despite the fact that micro-structure of equity markets is a widely addressed thematic, academic researchers just recently focused on bond markets. Providing an important source of capital for issuers and a significant range of securities for investors, corporate bond market is undoubtedly considered a crucial market. As shown in Table 1, corporate bond market accounts for nearly USD 8tr, which consists about half of the U.S. equity market. On the contrary, there are 66,000 securities, 8 times more than equity market.

Zero interest rate Federal Reverse policy has led to a growing interest in corporate bond markets over the past few years. In this way, a significant expansion of new issuances is recorded. Whereas the average net corporate bond insurance exceeded at the end of 2016 the amount of USD 400bn[1], it only accounted for USD 100bn at the end of 2007.

Following debt crisis of 2007, the stability of financial markets has been secured by bank-related regulations. Remarkable examples of these regulations are the Volcker Rule in mid-2012 and later the Basel 2.5&3, which all highlight the increased banks' capital and liquidity requirements. As a result of these reforms, many banks announced closures of their proprietary trading operations (e.g. J.P. Morgan and Goldman Sachs-September 2010, Morgan Stanley-January 2011, Bank of America-June 2011, Citigroup- January 2012[2]). The combination of financial crisis and these regulations lead to a historic sell-off of bond inventory possessed by primary dealers (approximately 80% for the period of 2007 to 2012). Decrease of dealer's inventory and increase of outstanding securities resulted in growing concerns regarding corporate bond markets' liquidity. Nevertheless, the actual turnover did not meet the decelerate rate of the estimations. Market Insight of McKinsey & Company and

[1] https://www.moneyandbanking.com/commentary/2017/4/17/revisiting-market-liquidity-the-case-of-us-corporate-bonds

[2] "JPMorgan shifting its proprietary trading desk," 9/27/2010, NY Times; "Goldman to close prop-trading unit,"9/4/2010, Wall Street Journal; "Morgan Stanley to spin off prop trading unit," 1/10/2011, Reuters; "Bank of America is shutting down Merrill's bond prop trading desk," 6/10/2011, Business Insider; "Citigroup exits proprietary trading, says most staff leave," 1/27/2012, Bloomberg;

Greenwich Associates of August 2013 points out the existence of actions which dealers get to cut inventories that hurt liquidity, but they were partially balanced by the increase of the velocity of the remaining dealers' inventory turnover. Finally the afterwards published studies did not meet a definite conclusion. As Janet Yellen, chair of the U.S. Federal Reserve, stated in 2015 "It's not clear whether there is or is not a problem [...] it's a question that needs further study"[3].

The development of research in both equity and bond markets can be entirely associated with the accessibility of quality intraday trade, quote, and/or order data ("tick" data) to empirical researchers. It is though a fact that corporate bond market is not particularly transparent and remains obsolete comparing to equity market. Corporate bond markets are considered relatively non-automated, not integrated and are characterized by opacity and lack of liquidity. To increase transparency in the corporate bond market, the National Association of Securities Dealers[4] (NASD) initiated on July 1st, 2002 a platform known as the Trade Reporting and Compliance Engine (TRACE). TRACE constitutes a transaction reporting and dissemination platform for all OTC trades. Specifically, dealers are bound to report their secondary market corporate bond trades through TRACE platform within a quarter minute lag of trade execution. Each reported trade, in turn, is disseminated to TRACE with a fifteen minute lag. In November 2008, TRACE started the dissemination of the reporting party side of all dealers' trades (i.e. customer or ATS buy from Dealer or sell to Dealer and interdealer trades). The time, size, and price of all US corporate bond trades are also publicly available among other TRACE data.

Despite these facts, corporate bond market remains a predominant dealer driven market with public transactions reporting only for executed trades and quotations accessible to a few market specialists. Furthermore, market is inherently illiquid with 45k trades per day, which corresponds for the 10.8% of outstanding securities. On the contrary equity market has approximately 40m trades, which corresponds for the 99.7% of outstanding securities. The daily dollar liquidity for corporate bond market is estimated at USD 27.5bn compared to equity market which averages USD 282.5bn.

---

[3] http://blogs.wsj.com/economics/2015/07/15/fed-chairwoman-janet-yellens-report-to-congress-live-blog/

[4] On July of 2007 NASD and the member regulation, enforcement and arbitration functions of the NYSE consolidated in a self-regulatory organization creating FINRA (Financial Industry Regulatory Authority). FINRA rules are approved by the SEC and enforced by themselves.

As far as corporate bond market is concerned, an intense activity in securities after their issuance is observed, which is followed by a dramatic drop or cease of their activity. It is a fact, that only a few securities show daily activity, which imperils the study of this market.

Corporate bond markets are relatively opaque concerning the pre-trade accessible information and quotation. However, there is lack of available data concerning the sell-side for Dealers to make the market, as there are more than 60,000 bonds outstanding but not all of them have “lit” quotes in related securities (not all the issuers of corporate bonds are listed on a Stock Exchange). Regarding buy-side, concerns arise thanks to wholesale trading happening entirely apart from retail trading and, as a result, creating two different markets for institutional and retail investors respectively. Therefore, retail investors are subject to higher prices than institutional ones (e.g. institutional investors pay on average about 5bps less than retail investors[5]). Additionally institutional investors raise concerns that public dissemination of their trades gives an advantage to retail investors only. They assert that the mid-term liquidity of the market is harmed by the fact that they have been reluctant to take large positions, since TRACE reveals their positions and their private information to the public.

Attempting to enhance the pre-trade transparency, liquidity and cost efficiency of the bond markets, regulations have been deployed to establish electronic trading in the corporate bond market. A consequence of relative growth in e-trading in bond markets is the decrease of transaction costs per bond compared to trade size and the increase of credit risk[6]. However, it is widely accepted that, the structural fragmentations of bond market will slow down the transition to electronic era. In 2013 only 20%[7] of corporate bond activity has mitigated to ATFs (Alternative Trading Systems), which in turn get through dealers.

[5] Tracing the Bond Market ,2016, KCG Market Insight
[6] Ciampi and Zitzewitz (2010), Adrian, Fleming, Shachar, and Vogt (2015)
[7] Corporate Bond E-Trading: Same Game, New Playing Field, 2013, McKinsey&Company and Greenwich Associates Report

Data and sample statistics

We based our analysis on Trace data provided by FINRA including daily aggregated trade data of the corporate bond market activity. More specifically, our dataset consists of corporate bonds participating in the formation of JPMorgan US Liquid Index (JULI Index). In this regard, our sample includes non-zero bullet bonds rated Baa3/BBB- or higher by Moody's and Standard & Poor's, respectively, with issue sizes of at least $300 million and issuer outstanding amount of fixed rate bonds at least $1bn. Each issue has a maturity longer than 13 months from the index-beginning date but no longer than 31 years.

Our sample combines bond level market data along with a wide range of bond’s specific characteristics. In particular, our dataset contains bond prices, cds spreads and cds bond basis, aggregate buying and selling daily trades (count of dealer buys and sells) and volumes per bond (volume of dealer buys and sells) as well as total traded volumes aggregated daily by size category. On the other hand bond attributes, which are available in our dataset, encompass coupon, maturity, issuer, credit rating status, business sector and issuer’s domicile among others.

Our initial sample consists of approximately 900.000 observations, but about 300.000 of which are not taken into consideration in our analysis, as they pertain to days without trading activity (i.e. zero traded volumes). Our final sample includes 4,287 unique CUSIPs of 958 issuers on 270 successive dates (Table 2-Panel A). Sample period ranges from January 30th, 2012 to June 3rd, 2013 including a 3 months gap between December 28th, 2012 and March 28th, 2013 due to lack of available transaction data.

In Tables (2) and (3), a statistical analysis is presented to show the allocation of our data in accordance to some of the statistic characteristics mentioned above. More specifically in the two first Columns of Tables (2) and (3) we show the allocation of our total observations (active trades) to business sector and issuer’s domicile respectively. Similarly, Columns (3) to (6) of the abovementioned Tables show the allocation of the total number of unique bonds and issuers respectively per business sector and issuer’s domicile. Furthermore, panels (A) and (B) of Table (4) report~~s~~ the allocation of active trades and unique bonds credit rating status and remaining maturity band respectively.

Furthermore, in Table (5) we display descriptive statistics concerning the average daily trades' data. As shown in Panel (A), the average number of daily trades is 4.92 and total traded volume per bond has a mean value of $2,836,619. The daily volume per bond that came from small, medium and large size trades averages $131,113, $2,048,131 and $1,638,002 respectively. It is essential to note that in our analysis we use the estimated dealer volumes, which constitute of the notional values of daily trades, corrected for the noise due to continuous reporting (e.g. trades cancellation, delayed trades reporting and trades with longer lead of time to be reported as block trades).

Moreover, we expand our analysis for aggregated data per bond issuer. Panel (B) presents the descriptive statistics on the aggregated data. We notice that on average there are 592 traded issuers with 3.66 active bonds per day. Additionally using the greater count of daily trades we recalculate the mean statistic having beforehand excluded observations with less than 5, 10 and 20 total trades per day at the three last Columns of Panel (B). As a result we approximate the most liquid issuers.

Finally, we categorize daily aggregate buy and sell volumes in three bands according to the size of total traded volume (less than 100K, between 100K & 1m and more than 1m). In Panel (A) of Table (6), we present the joint allocation of daily aggregate buy and sell volumes to the three volume bands. In the following two Panels we report descriptive statistics for daily buy and sell volumes per volume band.

Formation of variables

In this section, it is necessary to incorporate a series of variables in order to continue our analysis. Firstly, we define the daily fraction of buy trades of bond i in day t (denoted as $cp_{i,t}$) as the number of dealer's sales to the total dealer's activity of bond i in day t. That is,

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

We, also, employ the daily volumes in order to define the daily fraction of buying volume of bond i in day t, denoted as $vp_{i,t}$. That is,

$$vp_{i,t} = \frac{\$Buy_{i,t}}{\$Buy_{i,t} + \$Sell_{i,t}}$$

Furthermore, in Panel (C) of Table (4) we display some descriptive statistics of aforementioned variables. Similarly, we determine the above variables for aggregated data per issuer, that is, $iscp_{j,t}$ and $isvp_{j,t}$ respectively.

Given the fact that our sample contains volume information for the individual size of trades, we distinguish two investor groups, retail and institutional. Retail investors consist of small banks, corporations and retailers, whereas institutional investors include larger banks and funds. In particular, we approach retail investors' daily volume through the daily volume of small trades (< \$100K). Simultaneously, through other two categories (>\$1M volumes) we approach institutional investors' daily volume. In tis sense, we introduce a dummy variable to identify the investor category, which dominates the daily total traded volume for each bond. More specifically, the dummy variable (D_Inst) receives the value 1, when the total volume that arises from institutional investors exceeds 55% of the daily total volume for each bond/issuer.

Empirical Analysis-Hypothesis Development

In this section, we attempt to pursue patterns in daily activity of corporate bond market. We develop our analysis in two stages; during the first stage we test the existence of herding behavior in the corporate bond market. In particular, we examine whether institutional or retail investors follow other investors (institutionals or retailers) or themselves into and/or out of the same bonds. In the second stage we analyze the common objectives of herding behavior in the particular market as well as the extent to which are differentiated among institutional and retail investors. In doing so, we frame the following seven hypotheses that then we put to test.

Herding Behavior

1: Investors exhibit herding behavior on their daily trading activity
2: Institutional and retail investors do not exhibit same levels of herding tendency.
3a: Herding tendency of Institutional investors is not (entirely) attributed to the lack of liquidity in the corporate bond market.
3b: Herding tendency of Retail investors is not (entirely) attributed to the lack of liquidity in the corporate bond market.

Determinants of herding behavior

4: The level of herding behavior varies among bonds of different credit rating categories.
5: The level of herding behavior varies among bonds in different maturity bands.
6: The level of herding behavior varies between bond issued by Financial and Non-financial Institutions.
7: Herding behavior is expanded on issuer level.

For this purpose, we adopt Sias approach (2004) adjusted to our data. In particular, we calculate the standardized fraction of investors' daily demand in terms of trades and volumes utilizing cp and vp fraction respectively. That is,

$$\Delta cp_{i,t} = \frac{cp_{i,t} - E_t(cp_{i,t})}{sd_t(cp_{i,t})}$$

And

$$\Delta vp_{i,t} = \frac{vp_{i,t} - E_t(vp_t)}{sd_t(vp_{i,t})}$$

where $E_t(cp_{i,t})$ and $sd_t(cp_{i,t})$ are the daily cross-sectional average and standard deviation (across I securities) of $cp_{i,t}$ fraction respectively. Similarly, $E_t(_{vpi,t})$ and $sd_t(vp_{i,t})$ are calculated for $vp_{i,t.}$

Next, in order to directly capture the cross-sectional temporal dependence on investors' demand over successive days, we cluster our observations by time and run a pooled panel regression for each tested hypothesis. In doing so, we let our model to obtain cross-sectional effects (i.e. cross-sectional correlation on bonds' demand) whereas we assume that each day has a unique effect on market.

To enhance the robustness of our results we also utilize LSV approach. In this regard, we assure that our findings do not result of employed method (see the Appendix for detailed description of LSV approach).

Empirical Analysis

Hypothesis 1: Investors exhibit herding behavior on their daily trading activity

We frame the first hypothesis so as to explore whether investors follow other investors and/or themselves into and out of the same bonds on successive days. In doing so, we estimate a pool panel regression of the standardized fraction of buy trades of bond i in day t on its lagged term (denoted as $\Delta cp_{i,t}$).

$$\Delta cp_{i,t} = \alpha + \beta \Delta cp_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

The regression's results are presented in Column (1) of Table (6). In contrast to Sias approach our data are not balanced, as a consequence the intercept is differentiated than zero and averages 0.019. In this regard, we observe a buy drift on actively traded bonds of our sample. Moreover, we reported a strong positive relation between demand today and previous day, which averages 0.21.

Correspondingly, we use the Δvp and run the below regression so as to assess the superiority of the one model relative to the other. That is,

$$\Delta vp_{i,t} = \alpha + \beta \Delta vp_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

Our findings, presented in Column (2) of Table (6), confirm the previous positive relationship. In particular, we notice that the relation generated by trading volumes is much lower (averages 0.076) relative to the one generated by the number of trades.

All things considered, our analysis confirm the existence of a positive relation on the daily demand in corporate bond market. This positive pattern might be consistent with herding behavior. Moreover, we point that the magnitude of the reported positive relation is more severe in the examination of daily trades than volumes.

Hypotheses 2: Institutional and retail investors do not exhibit same levels of herding tendency

A question that arises naturally from the previous results pertains to whether both institutional and retail investors follows the same positive pattern in their trading activity. In a sense, the second hypothesis provides evidence of what extent the level of herding varies by each investor category, and ultimately whether institutional or retail investors do herd on daily basis.

In order to distinguish each investor's category behavior, we examine which category dominates the daily trades and trading volume for each bond. Firstly, we observe that, on average, the total number of trades is dominated by retail investors' trades, while the total volume of trades is mostly dominated by institutional investors' trades for each day and bond/issuer. For instance, if the total traded volume for a bond was \$300K (\$100K retail, \$200K institutional) and the total trades were 10, the maximum number of trades relative to institutional investors would be 2. It is clear that the total number of trades mainly arises from retail trades. In this regard, we re-define the results of the first regression as indication of retail investors' imitation behavior.

Despite the fact that the greater part of traded volume arises from institutional trades, we note many days where the actively traded bonds have hardly any institutional investors' participation (approximately the 1/3 of our sample). Moreover, we observe that the average institutional fraction in a bond dominated by institutional investors was 94%, whereas the average retail fraction was 6%. On the other hand, the average fraction of institutional and retail investors is 6% and 94% respectively to the bonds dominated by retail investors, as shown in Panel (D) of Table (6). In this sense, we employ the dummy variable D_{inst} coupled with the standardized vp fraction (denoted as $\Delta vp_{i,t}$) in regression (3) to test the second hypothesis.

$$\Delta vp_{i,t} = \alpha + \beta_1 \Delta vp_{i,t-1} + \beta_2 D_{inst_{i,t}} \Delta vp_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

Our results, as shown in Column (3) of Table (7), are interpreted as follows. The β1 coefficient presents the relation between the bonds' demand today and the previous day demand. This relation is attributed to the retail investors and averages 0.144 (statistically significant at confidence level of 1%). Correspondingly, the β2 coefficient shows a decrease of the positive relation between the bonds' demand on successive days for bonds dominated by institutional investors today and averages -0.10. By employing Wald test, we rejected the hypothesis that the joint effect of β1 and β2 efficient could be equal to zero in significance level of 1%. In other worlds, we report a lower yet highly significant positive relation between demand for bonds dominated by institutional investors today and the previous day demand. Consistent with our hypotheses 2a and 2b, the above finding indicates that both institutional and retail investors do herd.

To summarize, our results suggest that both institutional and retail investors follow other investors into and out of the same bonds. Yet, the magnitude of institutional investors' imitating behavior, as we expected, is significantly lower than of the retail investors.

Hypothesis 3

As we mentioned above, the corporate bond market is particularly illiquid. In an attempt to capture the more liquid part of bond market, we analyze the bonds participating in the formation of JULI Index. Despite the fact that we exclude the non-active bonds per day, we observe that there are few trades per bond (the sample median of the total daily trades per bond equals to three). As a consequence, herding behavior that we report might be driven by investors which return to complete a large trade that drained market liquidity the previous day.

To examine the validity of the abovementioned statement we frame the third hypothesis to test whether the reported positive relation on successive days' demand persist on liquid bonds. In doing so, we classify all bonds to 5 quintiles according to their total turnover over the examined period. In particular, the first quintile includes the most illiquid bonds (i.e. lowest total turnover), whereas the fifth quintile consists of the most liquid (i.e. highest total turnover). Next, we diversify our analysis for institutional and retail investors.

Hypothesis 3a: Herding tendency of Institutional investors is not (entirely) attributed to the lack of liquidity in the corporate bond market

To test whether the reported positive pattern on dominated by institutional investors bonds remains through more liquid quintiles, we run a regression of Δvp fraction on its lagged term coupled with 4 Dummies representing each quintile (except the 1st which we use as basis) only for the trades dominated by institutional investors' volume.

That is,

$$\begin{aligned} \Delta vp_{i,t} = \alpha + \beta_1 \Delta vp_{i,t-1} + \beta_2 TurnoverQ_2 \Delta vp_{i,t-1} + \beta_3 TurnoverQ_3 \Delta vp_{i,t-1} \\ + \beta_4 TurnoverQ_4 \Delta vp_{i,t-1} + \beta_5 TurnoverQ_5 \Delta vp_{i,t-1} + \varepsilon_{i,t} \quad (4) \end{aligned}$$

$$if\ Dinst = 1$$

Our results are presented in Column (1) of Panel (A)-Table (9). We observe that the β1 coefficient is positive and highly statistically significant at confidence level 1% (averages 0.038), whereas the coefficients of turnover quintiles are statistically insignificant. In this regard, we reject the hypothesis that the relation of successive days' demand is associated with the liquidity status of the bonds. Thus, we confirm that the observed positive pattern is not attributed (at least entirely) to institutional investors who return to complete a transaction that drained the market liquidity the previous day.

In this regard, we document a tendency of institutional investors to follow each other into or out of the same bonds.

Hypothesis 3b: Herding tendency of Retail investors is not (entirely) attributed to the lack of liquidity in the corporate bond market

In turn, to examine whether the reported positive pattern on dominated by retail investors bonds remains through more liquid quintiles, we run a regression of Δvp fraction on its lagged term coupled with 4 Dummies representing each quintile (except the 1st which we use as basis) only for the trades dominated by retail investors' volume. That is,

$$\Delta vp_{i,t} = \alpha + \beta_1 \Delta vp_{i,t-1} + \beta_2 TurnoverQ_2 \Delta vp_{i,t-1} + \beta_3 TurnoverQ_3 \Delta vp_{i,t-1} + \beta_4 TurnoverQ_4 \Delta vp_{i,t-1} + \beta_5 TurnoverQ_5 \Delta vp_{i,t-1} + \varepsilon_{i,t} \qquad (5)$$

$$if\ Dinst = 0$$

In addition, we take advantage of the fact that cp fraction is associated with retail investors' behavior, as we stated above, and we run the same regression employing Δcp fraction for all trades that have retail investor participation. That is,

$$\Delta cp_{i,t} = \alpha + \beta_1 \Delta vp_{i,t-1} + \beta_2 TurnoverQ_2 \Delta cp_{i,t-1} + \beta_3 TurnoverQ_3 \Delta cp_{i,t-1} + \beta_4 TurnoverQ_4 \Delta cp_{i,t-1} + \beta_5 TurnoverQ_5 \Delta cp_{i,t-1} + \varepsilon_{i,t} \qquad (6)$$

$$if\ retail\ volume_{i,t} > 0$$

The regressions' results are presented in Column (2) of Panels (A) and (B), Table (7). Both regressions report a sell drift on retail investor daily demand, since for both equations the intercept is statistically significant and averages -0.129 and -0.024 respectively. In addition, we observe a statistically greater relation on retail investors' successive days' demand for bonds of 1st quintile. The above findings confirm our hypothesis that a part of the reported positive pattern is attributed to liquidity issues of the examined market. However, our analysis suggests that the positive pattern remains in lower level for the bonds in intermediate quintiles. Furthermore, we observe that on the most liquid bonds (5th quintile bonds) the positive pattern remains equal or even exceeds the one of 1st quintile bonds, which could suggest that retail investors herd on more liquid issues.

Consistent with our results, LSV approach reports a positive relation on successive days' demand, which averages X, as we examine the number of trades and the traded volumes respectively. Interestingly, we observe that LSV approach reports a statistically significantly higher level of buy than sell herding concerning institutional investors. While, regarding retail investors sell herding measure is statistically higher at confidence level of 1%. On the contrary, our analysis reports a buy and sell drift for institutional and retail investors respectively. In this sense, our analysis provides more coherent results, since it takes into account the drift on each investor's group trade behavior. (LSV approach results are presented in Table (x)).

All things considered, our analysis draws the attention to four main points. Firstly, the pattern observed on trades dominated by institutional investors is not driven (at least not entirely) by liquidity issues of corporate bond market, since it is not affected by liquidity indices like as turnover. This finding is in support of our main hypothesis that institutional investors do herd. Secondly, it seems that for retail investors the corporate bond market is divided into two parts. The first one has hardly any institutional investors' participation, whereas the second one is dominated by institutional investors trades (in terms of daily traded volumes), as shown in Panel (D) of Table (6). In this regard, our analysis suggests that the positive pattern observed in the "first market" (1st and 2nd quintile) is due to the aforementioned liquidity issues of the market. On the other hand, the pattern observed on "second market" could not be attributed to liquidity issues, since there is a plenty of institutional investors' fund that can cover retail investors trades. In this sense, our findings provide evidence that retail investors follow the liquidity provided by institutional investors. Furthermore, by taking advantage of provided liquidity retailer investors exhibit herding behavior even on daily basis.

Last but not least, we observe a buy drift on institutional investors' trades whereas retail investors exhibit a sell trend. A possible interpretation could be associated with the fact that during the examined period regulatory reforms have made retail investors, as small banks, reluctant on holding their position (e.g. increases on capital and liquidity requirements). Whereas, the buy drift is consistent with the widely reported increasing trend of institutional investors to buy and hold. Additionally, in combination these patterns may suggest the existence of countercyclical institutional investors, who step in and benefit from the deviations in asset prices away from their fundamentals caused by retail investors.

In light of the finding that herding took place in the market for both investors' categories over the period investigated, we attempt to access the possible determinants of this behavior. In particular, we tested a wide range of empirically objectives which could be drive herding behavior.

Hypothesis 4: The level of herding behavior varies among bonds of different credit rating categories

A question that firstly arises is whether investors herding behavior varies through bonds' credit rating status. According to informational cascades theory of herding, there are periods of time, characterized by uncertainty and instability of financial markets, where investors choose to trust other investors' estimations disregarding their own private information, especially on riskier assets. In this regard, the issues that could be more dubious on their estimation, are related to the lower rated bonds. In this sense, due to uncertainty that prevails on financial markets over the examined period, we would expect the level of herding to be higher for BBB rated bond, whereas to cease for AAA rated bonds.

To put our hypothesis into test, we generate a dummy variable for each credit rating status (AAA, AA, A). Then, we examine how the relation between successive days' demand differs from BBB rated bonds to them on higher credit rating category. To do so, we employ AAA to A credit rating dummies coupled with Δvp fraction as shown below,

$$\Delta vp_{i,t} = \alpha + \beta_1 \Delta vp_{i,t-1} + \beta_2 D_{AAA_{i,t}} \Delta vp_{i,t-1} + \beta_3 D_{AA_{i,t}} \Delta vp_{i,t-1} + \beta_4 D_{A_{i,t}} \Delta vp_{i,t-1} + \varepsilon_{i,t} \quad (7)$$

The regression's results are presented in Panel (A) of Table (9). Regarding institutional investors, we do not report any statistically significant variation on their behavior due to the credit rating status of the traded bonds. In particular, the β1 coefficient averages 0.041 whereas the remaining coefficients are statistically insignificant. On the contrary, retail investors' behavior confirms our hypothesis, since we report greater levels of herding for lower credit rated bonds. This pattern is presented more severe in the examination of equation (7) employing Δcp fraction, as shown in Panel (B) of Table (9).

Hypothesis 5: The level of herding behavior varies among bonds in different maturity bands

Moving forward with our analysis, we examine whether the level of herding differs for bonds with longer maturities. To test this hypothesis we incorporate two dummy variables representing bonds with at least 5 years, 5 to 15 years and 15 to 30 years to maturity respectively. Next, we repeat the same analysis for Δvp and Δcp fraction. That is,

$$\Delta vp_{i,t} = \alpha + \beta_1 \Delta vp_{i,t-1} + \beta_2 rm_{5-15} \Delta vp_{i,t-1} + \beta_3 rm_{15-30} \Delta vp_{i,t-1} + \varepsilon_{i,t} \quad (8)$$

And

$$\Delta cp_{i,t} = \alpha + \beta_1 \Delta cp_{i,t-1} + \beta_2 rm_{5-15} \Delta cp_{i,t-1} + \beta_3 rm_{15-30} \Delta cp_{i,t-1} + \varepsilon_{i,t} \quad (9)$$

Regressions' results are shown in Panels (A) and (B) of Table (10). Regarding institutional investors, we observe a statistically significant increase of their herding behavior on medium-term bonds, since the β2 coefficient is positive and averages 0.011. As far as the retail investors are concerned, the level of herding increases as we examine greater maturity bands, since all coefficients are positive and highly statistically significant at both vp and cp analysis at confidence level 1%.

Hypothesis 6: The level of herding behavior varies between bond issued by Financial and Non-financial Institutions

Another interesting question that arises is whether the level of herding varies among bonds issued by Financial and Non-Financial Institutions. In this sense, we frame our 6th hypothesis by incorporating a dummy variable for Financial Institutions as follows:

$$\Delta vp_{i,t} = \alpha + \beta_1 \Delta vp_{i,t-1} + \beta_2 D_{FI} \Delta vp_{i,t-1} + \varepsilon_{i,t} \quad (10)$$

And

$$\Delta cp_{i,t} = \alpha + \beta_1 \Delta cp_{i,t-1} + \beta_2 D_{FI} \Delta cp_{i,t-1} + \varepsilon_{i,t} \quad (11)$$

Regressions' results, presented in Columns (1) to (3) of Table (11), indicate that both institutional and retail investors' behavior is more severe on bonds issued by Financial Institutions. This finding might be consistent with information cascade theory that we mentioned above. It is known that during the examined period financial institutions were in spotlight of both regulators and investors. In this regard, our results suggest that both institutional and retail investors' level of herding increases for bonds issued by Financial Institutions due to uncertainty that prevails in the market in relation to them.

Hypothesis 7: Herding behavior is expanded on issuer level

Finally, it would be interesting to examine whether the reported herding behavior is expanded on issuer level too. To do so, we frame our last hypothesis to test separately whether retail and institutional investors herd on the bonds of the same issuer. Correspondingly, we repeat our analysis to the aggregated by issuer daily traded volume and trades as well. In particular, we run a regression of $\Delta isvp_j$, fraction on its lagged term separately for the issuers of which the total daily traded volume is dominated by institutional and retail investors respectively. That is,

$$\Delta isvp_{i,t} = \alpha + \beta \Delta isvp_{i,t-1} + \varepsilon_{i,t} \qquad (12)$$

Likewise, we run a regression of Δiscp fraction on its lagged term requiring retail investors' participation.

$$\Delta iscp_{i,t} = \alpha + \beta \Delta iscp_{i,t-1} + \varepsilon_{i,t} \qquad (13)$$

The regression's results are presented in Column (1) of Table (12). In general, we report a positive pattern on institutional investors' demand for same issuer's bonds as well. However, the magnitude of beta coefficient is significantly lower than of equation (3), particularly it averages 0.016. Taking advantage of the fact that per issuer the total trades are much higher, we repeat our analysis by the additional requirement of at least 5, 10 and 20 total trades. By doing so, we attempt to capture more liquid issuers. As shown in Columns (2) to (4) of same Table, our results are not differentiated significantly yet remain. This finding suggests that institutional investors take into consideration the total performance of the issuer yet there is not only criterion. Regarding retail investor, we also report a positive relation on successive days' demand for bond of same issuer, which averages 0.11, not significantly different than the relation reported in examination of bonds individually. In addition, we observe that as we move to more actively traded issuers the level of the implying herding behavior of retail investors increases, as shown in Columns (2) to (4) of Panel (B)-Table (12). Interestingly, regarding retail investors, we note that there are few highly preferred issuers, particularly averages 3 on daily basis when we required more than twenty total trades. The above findings might suggest that for retail investors the overall performance of an issuer constitutes one of their main criteria.

Conclusions

Following recent financial crisis, herding behavior has played a profound role in amplifying stability risks. The prevalence of herding behavior has attracted interest of regulators, researchers and market participants in the asset management industry. Concerns have been also been raised about implications of such behavior on the financial markets stability, particularly in corporate bond market which constitutes a more vulnerable market due to liquidity issues among others.

In this dissertation we analyze herding behavior in the U.S. corporate bond market using daily aggregate transaction data from TRACE platform. As herding behavior we define the tendency of individual investors to follow each other into or out of the same bonds. We attempt to recognize micro-structure patterns in corporate bond market by directly examining the cross-sectional temporal dependence in investors' daily demand. We approximate daily demand by employing level transaction data, in particular aggregate buy and sell trades and volumes.

Our findings verify that investor herding has indeed taken place in the U.S. corporate bond market over the examined period (January 2012 up to June 2013). Particularly, our analysis suggests that the observed herding behavior arises more severe from retail investors than institutional ones. We support our findings by examining whether the reported positive relation on successive days' demand also persists on liquid bonds. As far as institutional investors are concerned, the positive pattern is not differentiated among bonds of different liquidity bands (in terms of overall turnover). This finding might be consistent with our hypothesis that institutional investors do herd on their daily trading activity. However, this pattern could also suggest that the corporate bond market is extremely illiquid, resulting to difficulties in assimilation institutional trades (i.e. large trades) on daily basis even for more liquid issues. On the contrary, regarding retail investors, we observe that retail investors' trading activity is divided into two "markets". The first one is characterized by illiquidity, due to the fact that institutional investors do not take part in it, while the second one is mainly dominated by institutional investors in terms of daily traded volume. In addition, we report a more severe level of herding on the most illiquid and liquid bonds respectively. As far as the trading of retail investors on the "first market" is concerned, our findings are attributed to the lack of liquidity which forces investors to return so as to complete their trades. Nevertheless, liquidity issues could not be the case concerning the reported increasing tendency of retail investors to follow other investors on the “second market”. In this regard, our results provide evidence that retail investors exhibit herding behavior by taking advantage of liquidity provided by institutional investors.

Furthermore, our analysis documents a sell drift on retail investors’ daily demand, whereas institutional investors exhibit a buy drift on their daily demand. A possible interpretation could be associated with the fact that during the examined period regulatory reforms have made retail investors as small banks reluctant on holding their position (e.g. increases on capital and liquidity requirements). On the contrary, the buy drift is consistent with the widely reported increasing trend of institutional investors to buy and hold. Moreover, in combination these patterns may suggest the existence of countercyclical institutional investors, who step in and benefit from the deviations in asset prices away from their fundamentals caused by retail investors.

Additionally, to determine the tendency of investors to trade in herds, we examine how the extent of herding interacts with a wide range of empirical factors, such as credit rating status, remaining maturity and issuer’s sector. Specifically, the analysis of different credit rating categories reveals that regarding retail investors the average level of herding is much higher for lower credit rated bonds. Interestingly enough we find no such relation for institutional investors. As far as remaining maturity is concerned, we observe that retail investors increase their herding tendency across longer maturity bonds. On the other hand, institutional investors’ herding behavior is reported more intensive on medium-term bonds. Our results also document that retail and institutional investors’ level of herding increases for bonds issued by Financial Institutions. All of these findings are consistent with information cascade theory, which suggests herding as a rational behavior of investors during market uncertainty.

Last but not least, our empirical analysis provides evidence that both institutional and retail investors herding behavior is expanded on issuer level. In particular, we document same level of retailers herding behavior concerning individual bonds and aggregately on issuer level. In this sense, our results suggest that retail investors focus their attention on issuer’s performance. On the contrary, institutional investors hone their focus on individual bond performance, yet taking into account issuer's performance.

Appendix

In order to enhance our analysis we also adopt the widely-used herding measure proposed by LSV, to estimate the extent of herding behavior on corporate bond market separately for institutional and retail investors as well as jointly. Particularly, we calculate the herding measure (HM) of bond i in day t as follows:

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

Where the term $p_{i,t}$ is the proportion of buyers to the total active traders of bond i in day t. That is,

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

Similarly, we approximate the expected level of buy intensity $E[p_{i,t}]$[8] using the market-wide intensity of buy trades as shown below:

$$E[p_t] = \frac{\sum_{i=1}^{N} \#\text{ of } Buy_{i,t}}{\sum_{i=1}^{N} \#\text{ of } Buy_{i,t} + \sum_{i=1}^{N} \#\text{ of } Sell_{i,t}}$$

The first term $\left|p_{i,t} - E[p_t]\right|$, measures how much the trading pattern of bond i varies from the general trend of the market in day t.

The second term, $AF_{i,t}$, constitutes an adjustment factor to figure for the fact that the absolute value of $p_{i,t} - E[p_t]$, is always greater than zero. Under the null hypothesis of no herding, the adjustment factor ensures that herding measure $HM_{i,t}$ for bond i in day t is anticipated to be zero. It is also essential to note that the count of Buy_t trades follows a binomial distribution, $\sim B(n_{i,t}, E(p_t))$, where $n_{i,t}$= # of $Buy_{i,t}$ +# of $Sell_{i,t}$ and $E(p_t)$ is market wide intensity. Thus, a positive and significant herding measure will indicate the existence of herding in the corporate bond market.

To differentiate between buy herding and sell herding, we employ Wermers approach(1999). In doing so, we define a buy herding measure (henceforth BHM) for bonds with a higher proportion of buyers than the market average and a sell herding

[8] Note that pi,t is similarly calculated as cpi,t fraction of Sias Approach whereas E[pi,t] and sd[pi,t] are differentiated.

measure (SHM henceforth) for bonds with lower proportion of buyers than the market average. That is,

$$BHM_{i,t} = HM_{i,t} \;\; if \; p_{i,t} > E[p_{i,t}]$$

And

$$SHM_{i,t} = HM_{i,t} \; if \; p_{i,t} < E[p_{i,t}]$$

By design, for a given bond in a given day, there is either a BHM or a SHM herding measure (but not both). Under the null hypothesis of no buy (sell) herding, BHM (SHM) of a bond in a given day is expected to be zero. If trading investors sell in herds more frequently than they buy in herds, the average SHM (denoted $\overline{SHM}$) will be significantly greater than the average (denoted $\overline{BHM}$)[9].

Another way to measure herding is to use the par amount of buy and sell trades instead the number of trades (Dollar-based Herding Measure based on LSV(1992) and Wermers(1999)). We incorporate this method as well by employing the daily estimated dealer volumes. Our dollar-based herding measure is defined as follows:

$$DHM_{i,t} = \frac{|Buy\ Amount_{i,t} - Sell\ Amount_{i,t}|}{Buy\ Amount_{i,t} + Sell\ Amount_{i,t}}$$

To differentiate between buy herding and sell herding, we also define a dollar-based buy herding measure (henceforth DBHM) for bonds with larger par amount of purchases than sales and sell herding measure (DSHM henceforth) for bonds with larger par amount of sales than purchases. That is,

$$DBHM_{i,t} = DHM_{i,t}, if\ Buy\ Amount_{i,t} > Sell\ Amount_{i,t}$$

$$SBHM_{i,t} = DHM_{i,t}, if\ Buy\ Amount_{i,t} < Sell\ Amount_{i,t}$$

[9] Note that when we calculate BHM or SHM, the adjustment factor is recalculated conditional on $p_{i,t}$>E[$p_{i,t}$] or $p_{i,t}$<E[$p_{i,t}$]. For the case when $p_{i,t}$=E[$p_{i,t}$], neither BHM nor SHM is calculated for the corresponding day.

References

Adrian, T., Fleming, M., Shachar, O., & Vogt , E. (2015). *Has U.S. Corporate Bond Market Liquidity Deteriorated?* Liberty Street Economics.

Avery, C., & Zemsky, P. (1998). Multidimensional uncertainty and herd behavior in financial markets. *The American Economic Review, 88*(4), 724-748.

Baddeley , M., Curtis, A., & Wood, R. (2004). *An Introduction to Prior Information Derived from Probabilistic Judgments: Elicitation of Knowledge, Cognitive Bias and Herding* (Vol. 239). London: Special Publications.

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

Barberis , N., Shleifer , A., & Vishny, R. (1998). A model of investor sentiment, Journal of Financial Economics. *49*(3), 307-343.

Barberis, N., Shleifer, A., & Vis, R. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(3), 307-343.

Bikhchandani , S., & Sharma, S. (2001). Herd behavior in financial markets. *IMF Staff Papers, 47*(3), 279-310.

Black, F. (1986). Noise. *Journal of Finance, 41*(3), 529-543.

Cai, F., Hany, S., & Li, Y. (2016). *Institutional Herding and Its Price Impact: Evidence from the Corporate Bond Market.* Board of Governors of the Federal Reserve System, Working Paper.

Cecchetti, S. G., & Schoenholtz, K. L. (2017). Revisiting Market Liquidity: The Case of U.S. Corporate Bonds. Money and Banking. Retrieved from https://www.moneyandbanking.com/commentary/2017/4/17/revisiting-market-liquidity-the-case-of-us-corporate-bonds

Christie , W. G., & Huang, R. D. (1995). Following the pied piper: do individual returns herd around the market? *Financial Analysts Journal, 51*(4), 31-37.

Ciampi, P., & Zitzewitz, E. (2010). *Corporate and Municipal Bond Trading Costs During the Financial Crisis.* White Paper: Data Pricing and Reference Data Inc.

Cipriani , M., & Guarino, A. (2005). Cipriani, M. aHerd behavior in a laboratory financial market, ,. *The American Economic Review, 95*(5), 1427-1443.

Daniel , K., Hirshleifer , D., & Subrahmanyam , A. (1998). Investor psychology and investor security market under – and overreactions, *Journal of Finance, 53*(6), 1839-1886.

Doug, A. (2014). RBC Exits Half Its Prop-Trading Strategies as Volcker Rule Looms. Bloomberg. Retrieved from https://www.bloomberg.com/news/articles/2014-12-03/rbc-exits-half-its-prop-trading-strategies-as-volcker-rule-looms

Economou, F., Kostakis, A., & Philippas, N. (2011). Cross-country effects in herding behavior:evidence from four south European markets. *Journal of International Financial Markets,Institutions and Money, 21*(3), 443-460.

Froot , K. A., Scharfstein , D. S., & Stein , J. C. (1992). Herd on the street: informational inefficiencies in a market with short-term speculation. *The Journal of Finance, 47*(4), 1461-1484.

Galariotis , E. C., Rong , W., & Spyrou, S. I. (2015). Herding on fundamental information: A comparative study. *Journal of Banking and Finance, 50*, 589-598.

Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. *Journal of Empirical Finance, 11*(5), 681-694.

Graham, J. R. (1999). Herding among investment newsletters: theory and evidence, *The Journal of Finance, 54*(1), 237-268.

Griffin, D. (2012). Citigroup Exits Proprietary Trading, Says Most Staff Leave. Bloomberg. Retrieved from https://www.bloomberg.com/news/articles/2012-01-27/citigroup-says-most-proprietary-trading-employees-to-leave-as-desk-closed

Grinblatt, M., Titman , S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behavior. *The American Economic Review, 85*(5), 1088-1105.

Henker, J., Henker, T., & Mitsios, A. (2006). Do investors herd intraday in Australian equities? *International Journal of Managerial Finance, 2*(3), 196-219.

Holmes, P., Kallinterakis, V., & Leite Ferreira, M. (2013). Herding in a concentrated market:a question of intent. *European Financial Management, 19*(3), 497-520.

Hong , H., & Stein , J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance, 54*(6), 2143-2184.

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance, 11*(4), 585-616.

Iihara, Y., Kiyoshi, H., & Tokunaga, T. (2001). Investors’ herding on the Tokyo stock exchange, *International Review of Finance, 2*(1-2), 71-98.

Keynes, J. M. (1936). *The General Theory of Employment, Interest and Money.* London: Macmillan Publications.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics, 32*(1), 23-43.

McKinsey & Company and Greenwich Associates. (2013). Corporate Bond E-Trading: Same Game, New Playing Field. Retrieved from https://r.search.yahoo.com/_ylt=AwrBT0cSBBtagssAorVXNyoA;_ylu=X3oD

MTByOHZyb21tBGNvbG8DYmYxBHBvcwMxBHZ0aWQDBHNlYwNzcg--/RV=2/RE=1511748754/RO=10/RU=https%3a%2f%2fwww.mckinsey.com%2f~%2fmedia%2fmckinsey%2fdotcom%2fclient_service%2ffinancial%2520services%2fl

Rajan, R. G. (2006). Has finance made the world riskier? *European Financial Management, 12*(4), 499-533.

Reddy, S., Zumbrun, J., & Harri, D. (2015). Fed Chairwoman Janet Yellen's Report to Congress — Live Analysis. The Wall Street Journal. Retrieved from https://blogs.wsj.com/economics/2015/07/15/fed-chairwoman-janet-yellens-report-to-congress-live-blog/

Scharfstein , D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review, 80*(3), 465-479.

Shleifer , A., & Summers, L. H. (1990). The noise trader approach to finance, The Journal of Economic Perspectives. *4*(2), 19-33.

Sias, R. W. (2004). Institutional herding. *Review of Financial Studies, 17*(1), 165-206.

Spyrou, S. (2013). Herding in financial markets: a review of the literature. *Review of Behavioral Finance, 5* (2), 175-194.

Trueman, B. (1994). Analyst forecasts and herding behavior,. *Review of Financial Studies, 7*(1), 97-124.

Wachtel , K. (2011). Bank of America shutting down bond prop-trading desk. Business Insider. Retrieved from http://www.businessinsider.com/bank-of-america-shutting-down-bond-prop-trading-desk-steve-padovano-srini-dhulipala-2011-6

Walter , A., & Weber, F. M. (2006). Herding in the German mutual fund industry. *European Financial Management, 12*(3), 375-406.

Wermers , R. (1999). Mutual fund herding and the impact on stock prices. *The Journal of Finance, 54*(2), 581-622.

Wylie, S. (2005). Fund manager herding: a test of the accuracy of empirical results using UK data. *The Journal of Business, 78*(1), 381-403.

Tables

Table 1

Corporate Bond vs Equity Market

	Corporate Bonds	**Equities**
Market Size	$ 8tr	$ 20tr
Liquidity (daily $)	$27.5bn	$282.5 bn
Number of securities	~66,000	~8,000 NMS[10] Stocks
Breadth (securities traded/day)	~7,500 (10.8%)	~8,000 (99.7%)
Liquidity (trades/day)	~45K	~40m
Price discovery (trades/day/security)	16	~4K
Trading Regulated by	SEC, FINRA	SEC, FINRA
Exchange	no	yes
Executable Quotes	Mostly RFQ (Request for quotation)	Executable quotes for 99% of securities
Consolidated tape	TRACE	SIP[11]
Tape latency	Up to 15 minutes (1 day for Block trades)	~0.0008 seconds: SIP Up to 10 seconds:TRF[12]
How are they traded	Exchange (~0%) ATS[13] (20%) OTC/Phone (80%)	Exchanges (66%) ATS (15%) OTC(19%)
Reporting covers	Corporate bonds	All listed stocks
Number of trading venues	OTC+ ~22 ATSs	Around 50 (Exchanges & ATS)
Trades reported since	2002	1975

Source: SIFMA, Bloomberg, FINRA, BATS, KCG

---

[10] National Market System
[11] Session Initiation Protocol
[12] Trade Reporting Facility
[13] Alternative Trading System

Table 2

Panel A: Sample Data

Total Observations	585,450
Number of CUSIPs	4,287
Number of Issuers	958
Number of observed dates	270

Panel B: Allocation by business sector of:

	Total Obs.		**Bonds**		**Issuers**	
	Freq.	%	Freq.	%	Freq.	%
Banks	124,268	21.23%	760	17.73%	173	18.06%
Basic_Industries	37,999	6.49%	282	6.58%	71	7.41%
Capital Goods	28,757	4.91%	246	5.74%	51	5.32%
Consumer	54,285	9.27%	414	9.66%	92	9.60%
Diversified	4,356	0.74%	28	0.65%	3	0.31%
Energy	63,367	10.82%	505	11.78%	117	12.21%
Healthcare Pharmaceuticals	47,704	8.15%	363	8.47%	66	6.89%
Insurance	32,284	5.51%	207	4.83%	59	6.16%
Media Entertainment	31,812	5.43%	200	4.67%	33	3.44%
Property Real Estate	13,220	2.26%	131	3.06%	40	4.18%
Retail	29,235	4.99%	189	4.41%	33	3.44%
Technology	32,957	5.63%	214	4.99%	46	4.80%
Telecoms	32,925	5.62%	179	4.18%	35	3.65%
Transportation	11,497	1.96%	107	2.50%	20	2.09%
Utilities	40,784	6.97%	462	10.78%	119	12.42%
Total	585,450	100.00%	4,287	100.00%	958	100.00%

Table 3

Bonds allocation by issuer domicile

	Total Obs.		Bonds		Issuers	
	Freq.	%	Freq.	%	Freq.	%
United Arabic Emirates	22	0.00%	2	0.05%	2	0.21%
Australia	4,890	0.84%	44	1.03%	13	1.36%
Belgium	5,611	0.96%	36	0.84%	6	0.63%
Brazil	6,503	1.11%	42	0.98%	12	1.25%
Canada	20,656	3.53%	186	4.34%	42	4.38%
Switzerland	12,403	2.12%	78	1.82%	24	2.51%
Chile	694	0.12%	6	0.14%	3	0.31%
China	198	0.03%	7	0.16%	3	0.31%
Colombia	1,194	0.20%	6	0.14%	3	0.31%
Germany	2,262	0.39%	18	0.42%	6	0.63%
Denmark	31	0.01%	2	0.05%	1	0.10%
Spain	3,523	0.60%	18	0.42%	5	0.52%
Finland	171	0.03%	2	0.05%	1	0.10%
France	6,183	1.06%	40	0.93%	15	1.57%
United Kingdom	23,538	4.02%	156	3.64%	30	3.13%
Greece	29	0.00%	1	0.02%	1	0.10%
Ireland	1,078	0.18%	8	0.19%	2	0.21%
Israel	1,576	0.27%	9	0.21%	5	0.52%
India	6	0.00%	1	0.02%	1	0.10%
Italy	2,656	0.45%	12	0.28%	2	0.21%
Japan	1,306	0.22%	15	0.35%	5	0.52%
Korea	9	0.00%	3	0.07%	2	0.21%
Luxembourg	1,927	0.33%	14	0.33%	2	0.21%
Mexico	3,787	0.65%	26	0.61%	6	0.63%
Netherlands	6,004	1.03%	43	1.00%	11	1.15%
Norway	1,761	0.30%	16	0.37%	3	0.31%
Russian Federation	10	0.00%	1	0.02%	1	0.10%
Sweden	671	0.11%	7	0.16%	3	0.31%
Singapore	1	0.00%	1	0.02%	1	0.10%
United States	476,037	81.31%	3,483	81.25%	745	77.77%
South Africa	713	0.12%	4	0.09%	2	0.21%
Total	585,450	100.00%	4,287	100.00%	958	100.00%

Table 4

Panel A: Allocation by credit rating status of:

	Total Obs.		**Bonds**	
	Freq.	%	Freq.	%
AAA	4,999	0.85%	1,691	0.00%
AA	44,417	7.59%	316	0.00%
A	241,141	41.19%	32	0.00%
BBB	294,893	50.37%	2,248	0.00%
Total	585,450	100.00%	4,287	100.00%

Panel B: Allocation by remaining maturity band of:

	Total Obs.		**Bonds**	
	Freq.	%	Freq.	%
lower than 5 years	245,907	42.01%	1,572	36.67%
5 to 15 years	215,584	36.83%	1,703	39.72%
15 to 30 years	123,857	21.16%	1,012	23.61%
Total	585,450	100.00%	4,287	100.00%

Panel C: cp and vp Statistics

	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
cp	585,450	0.4758357	0.3723995	0	1
vp	585,450	0.4900398	0.4185846	0	1
iscp	159,888	0.4862068	0.309618	0	1
isvp	159,888	0.5067449	0.3645026	0	1

Table 5

Panel A: Trades Statistics

	Obs	Mean	Std. Dev.	Min	Max
Average number of CUSIPs per day	270	2,168	231	432	2,700
Average number of dealer trades per day	270	4.92	0.62	1.84	6.73
Average volume of dealer trades per day	270	2,836,619	629,225	389,729	4,532,702
Average daily aggregate volume of trades sized less than100K	270	131,113	20,056	43,134	181,453
Average daily aggregate volume of trades sized between 100K & 1m	270	2,048,131	414,059	314,171	3,041,926
Average daily aggregate volume of trades sized higher than 1m	270	1,638,002	481,464	134,311	2,979,798

Panel B: Trades Statistics aggregated by Issuer Statistics

						Mean (taking into account only issuers with)		
	Obs	Mean	Std. Dev.	Min	Max	≥ 5 Total trades	≥ 10 Total trades	≥ 20 Total trades
Average number of Issuers per day	270	592	54	111	705	329	204	114
Average number of CUSIPs per Issuer	270	3.66	0.15	2.56	3.96	5.50	11.60	13.60
Average number of dealer trades per day	270	18.06	2.57	4.71	24.83	30.73	88.11	111.90
Average volume of dealer trades per day	270	10,400,000	2,402,311	1,162,738	16,700,000	17,300,000	48,600,000	60,800,000
Average daily aggregate volume of trades sized less than100K	270	480,860	79,458	110,388	670,846	825,386	2,462,200	3,153,636
Average daily aggregate volume of trades sized between 100K & 1m	270	7,523,682	1,600,830	937,314	10,900,000	12,600,000	35,000,000	43,900,000
Average daily aggregate volume of trades sized higher than 1m	270	6,014,331	1,797,360	400,709	10,800,000	10,100,000	31,500,000	39,800,000

Table 6

Panel A: Statistics for Daily Sell Volumes per Bond

	Sell Vol. < 100K	100K ≤ Sell Vol. < 100m	Sell Vol. ≥ 100m	Total
Buy Vol.< 100K	30.05%	12.72%	6.74%	49.50%
100K ≤ Buy Vol. < 100m	14.74%	7.75%	4.43%	26.93%
Buy Vol. ≥ 100m	8.54%	4.56%	10.47%	23.57%
Total	53.33%	25.03%	21.63%	100.00%

Panel B: Statistics for Daily Buy Volumes per Bond

	Obs	Mean	Std. Dev.	Min	Max
Buy Vol.< 100K	283,214	15,081	23,648	0	99,000
100K ≤ Buy Vol. < 100m	162,728	370,131.90	235,759.00	100,000.00	999,000.00
Buy Vol. ≥ 100m	139,508	5,566,935	6,863,485	1,000,000	293,000,000
Total	585,450	1,436,730	4,074,289	0	293,000,000

Panel C: Statistics for Daily Sell Volumes per Bond

	Obs	Mean	Std. Dev.	Min	Max
Sell Vol.< 100K	306,777	18,275	24,398	0	99,000
100K ≤ Sell Vol. < 100m	151,323	350,023.90	230,831.60	100,000.00	999,000.00
Sell Vol. ≥ 100m	127,350	6,113,093	7,181,723	1,000,000	232,000,000
Total	585,450	1,429,798	4,165,303	0	232,000,000

Table 7

Panel A: Investors'volume fraction for Institutional and Retail dominated bonds Statistics

	Obs	Percent		Obs	Mean	Std. Dev.	Min	Max
Retail Dominated Bonds	191,578	32.72%	Retail fraction	191,542	95.55%	13.22%	45.00%	100.00%
			Institutional fraction	191,542	4.45%	13.22%	0.00%	55.00%
Institutional Dominated Bonds	393,872	67.28%	Retail fraction	393,806	6.39%	10.07%	0.00%	45.00%
			Institutional fraction	393,806	93.61%	10.07%	55.00%	100.00%

Panel B: Average % of Institutional dominated trades per each turnover quintile

	Obs.	Mean Persentage
Turnover Q1	117,269	4.99%
Turnover Q2	117,008	49.46%
Turnover Q3	116,983	86.36%
Turnover Q4	117,100	96.37%
Turnover Q5	117,090	99.30%

Table 8

	$\Delta cp_{i,t}$		$\Delta vp_{i,t}$		$\Delta vp_{i,t}$	
constant	0.020	***	0.024	***	0.025	***
	(14.31)		(16.68)		(17.67)	
$\Delta cp_{i,t-1}$	0.212	***				
	(146.52)					
$\Delta vp_{i,t-1}$			0.076	***	0.144	
			(51.80)		(56.01)	
$Dinst_{i,t}\Delta vp_{i,t-1}$					-0.101	***
					(-32.07)	
overall Rsq	0.045		0.006		0.008	
Number of Obs	456,625		456,625		456,625	
Number of Groups	269		269		269	
Avg Obs per Groups	1,698		1,698		1,698	

Table 9

Panel A

		Institutional Dominated Bonds		Retail Dominated Bonds	
		$\Delta vp_{i,t}$		$\Delta vp_{i,t}$	
constant		0.095	***	-0.129	***
		(55.16)		(-49.28)	
$\Delta vp_{i,t-1}$		0.038	***	0.174	***
		(4.25)		(21.42)	
$\Delta vp_{i,t-1}$	Turnover_Q2	-0.004		-0.030	***
		(-0.41)		(-3.02)	
	Turnover_Q3	-0.002		-0.064	***
		(-0.23)		(-6.58)	
	Turnover_Q4	0.000		-0.066	***
		(-0.04)		(-6.8)	
	Turnover_Q5	0.011		0.009	
		(1.17)		(0.94)	
overall Rsq		0.002		0.020	
Number of Obs		313,650		142,975	
Number of Groups		269		269	
Avg Obs per Groups		1,166		532	

Panel B

		Retail volume$_{i,t}$>0	
		$\Delta cp_{i,t}$	
constant		-0.024	***
		(-16.82)	
$\Delta cp_{i,t-1}$		0.225	***
		(39.09)	
$\Delta cp_{i,t-1}$	Turnover_Q2	-0.002	
		(-0.27)	
	Turnover_Q3	-0.025	***
		(-3.69)	
	Turnover_Q4	-0.007	
		(-1.01)	
	Turnover_Q5	0.148	***
		(22.92)	
overall Rsq		0.078	
Number of Obs		371,822	
Number of Groups		269	
Avg Obs per Groups		1,382	

Table 10

Panel A: LSV Herding Measures (in percent)

		Obs	Mean	Std. Err.	[99% Conf. Interval]	
Institutional Dominated trades	HM	393,872	2.61%	0.03%	2.54%	2.67%
	BHM	213,516	16.73%	0.04%	16.63%	16.82%
	SHM	180,356	14.54%	0.03%	14.45%	14.63%
	BHM-SHM		2.19%	0.05%	2.06%	2.32%
Retail Dominated trades	HM	191,578	3.38%	0.03%	3.30%	3.47%
	BHM	80,363	20.30%	0.06%	20.14%	20.45%
	SHM	111,215	20.39%	0.04%	20.29%	20.49%
	BHM-SHM		-0.09%	0.07%	-0.27%	0.09%
Total trades	HM	585,450	2.86%	0.02%	2.81%	2.91%
	BHM	293,879	17.70%	0.03%	17.62%	17.79%
	SHM	291,571	16.77%	0.03%	16.70%	16.84%
	BHM-SHM		0.04%	0.83%	1.04%	17.19%

Table 11

Panel A

	Institutional Dominated Bonds		Retail Dominated Bonds	
	$\Delta vp_{i,t}$		$\Delta vp_{i,t}$	
constant	0.095	***	-0.128	***
	(55.64)		(-49.24)	
$\Delta vp_{i,t-1}$	0.041	***	0.149	***
	(16.19)		(41.03)	
$\Delta vp_{i,t-1}$ $AAA_{i,t}$	-0.007		-0.092	***
	(-0.39)		(-3.66)	
$AA_{i,t}$	0.009		-0.057	***
	(1.37)		(-5.32)	
$A_{i,t}$	-0.003		-0.015	***
	(-0.78)		(-2.74)	
overall Rsq	0.002		0.020	
Number of Obs	313,650		142,975	
Number of Groups	269		269	
Avg Obs per Groups	1,166		532	

Panel B

		Retail volumei,t>0	
		$\Delta cp_{i,t}$	
constant		-0.013	***
		(-9.14)	
$\Delta cp_{i,t-1}$		0.281	***
		(130.05)	
$\Delta cp_{i,t-1}$	$AAA_{i,t}$	-0.115	***
		(-7.4)	
	$AA_{i,t}$	-0.075	***
		(-12.36)	
	$A_{i,t}$	-0.030	***
		(-9.12)	
overall Rsq		0.073	
Number of Obs		371,822	
Number of Groups		269	
Avg Obs per Groups		1,382	

Table 12

Panel A

	Institutional Dominated Bonds	Retail Dominated Bonds
	$\Delta vp_{i,t}$	$\Delta vp_{i,t}$
constant	0.095 ***	-0.126 ***
	(55.56)	(-48.64)
$\Delta vp_{i,t-1}$	0.039 ***	0.101 ***
	(14.29)	(25.58)
$\Delta vp_{i,t-1}$ $Qrmy2_{i,t}$	0.011 ***	0.041 ***
	(2.62)	(7.20)
$Qrmy3_{i,t}$	-0.007	0.120 ***
	(-1.47)	(16.43)
overall Rsq	0.002	0.021
Number of Obs	313,650	142,975
Number of Groups	269	269
Avg Obs per Groups	1,166	532

Panel B

	Retail volume$_{i,t}$>0
	$\Delta cp_{i,t}$
constant	-0.011 ***
	(-7.88)
$\Delta cp_{i,t-1}$	0.219 ***
	(92.70)
$\Delta cp_{i,t-1}$ $Qrmy2_{i,t}$	0.055 ***
	(15.99)
$Qrmy3_{i,t}$	0.120 ***
	(27.88)
overall Rsq	0.074
Number of Obs	371,822
Number of Groups	269
Avg Obs per Groups	1,382

Table 13

		Institutional Dominated Bonds	Retail Dominated Bonds	Retail $volume_{i,t}>0$
		$\Delta vp_{i,t}$	$\Delta vp_{i,t}$	$\Delta cp_{i,t}$
constant		0.095 ***	-0.128 ***	-0.012 ***
		(55.64)	(-49.15)	(-8.41)
$\Delta vp_{i,t-1}$		0.037 ***	0.133 ***	
		(17.96)	(44.54)	
$\Delta vp_{i,t-1}$	Dfinancial	0.012 ***	0.019 ***	
		(3.15)	(3.09)	
$\Delta cp_{i,t-1}$				0.24 ***
				(135.59)
$\Delta cp_{i,t-1}$	Dfinancial			0.069 ***
				(19.53)
overall Rsq		0.002	0.021	0.073
Number of Obs		313,650	142,975	371,822
Number of Groups		269	269	269
Avg Obs per Groups		1,166	532	1,382

Table 15

Panel A: Institutional Dominated Bonds

		Total trades per Issuer≥5	Total trades per Issuer≥10	Total trades per Issuer≥20
	$\Delta isvp_{i,t}$	$\Delta isvp_{i,t}$	$\Delta isvp_{i,t}$	$\Delta isvp_{i,t}$
constant	0.051 ***	0.043 ***	0.041 ***	0.034 ***
	(18.52)	(15.28)	(13.47)	(9.69)
$\Delta isvp_{i,t-1}$	0.016 ***	0.022 ***	0.022 ***	0.033 ***
	(5.49)	(6.47)	(5.37)	(5.83)
overall Rsq	0.0003	0.001	0.001	0.002
Number of Obs	112,305	78,572	51,265	29,589
Number of Groups	269	269	269	269
Avg Obs per Groups	418	292	191	110

Panel B: Retail Dominated Bonds

		Total trades per Issuer≥5	Total trades per Issuer≥10	Total trades per Issuer≥20
	$\Delta isvp_{i,t}$	$\Delta isvp_{i,t}$	$\Delta isvp_{i,t}$	$\Delta isvp_{i,t}$
constant	-0.118 ***	0.008 ***	0.137 ***	0.241 ***
	(-17.31)	(0.86)	(9.8)	(9.92)
$\Delta isvp_{i,t-1}$	0.116 ***	0.154 ***	0.163 ***	0.195 ***
	(18.63)	(15.12)	(9.62)	(5.43)
overall Rsq	0.013	0.029	0.039	0.063
Number of Obs	26,714	7,670	2,896	841
Number of Groups	269	269	268	253
Avg Obs per Groups	99	29	11	3

Extended Summary in Greek- Ευρεία Περίληψη στα Ελληνικά

Σκοπός της παρούσας εργασίας είναι η εξέταση της συμπεριφοράς της αγέλης (herding behavior) στη δευτερογενή εξωχρηματιστηριακή αγορά εταιρικών ομολόγων της Αμερικής. Η έννοια της αγελαίας συμπεριφοράς, ή όπως είναι ευρέως διαδεδομένη με τον όρο «herding», έχει αποτελέσει αντικείμενο πολλών κοινωνικών επιστημών. Επίσης, το φαινόμενο αυτό έχει μελετηθεί ιδιαίτερα από την επιστήμη της συμπεριφορικής χρηματοοικονομικής. Ουσιαστικά, στα χρηματοοικονομικά με τον όρο «herding» αναφερόμαστε στην τάση των επενδυτών να μιμείται ο ένας τον άλλον στην αγορά ή πώληση των ίδιων τίτλων κατά τη διάρκεια μιας χρονικής περιόδου.

Κατά καιρούς έχουν προταθεί διάφορα μέτρα, καθώς και αρκετές θεωρίες που εξηγούν το συγκεκριμένο φαινόμενο. Οι θεωρίες αυτές προσεγγίζουν την αγελαία συμπεριφορά, είτε ως εξωτερικότητα μιας ορθολογικής επιλογής των επενδυτών σε σχέση με τη μεγιστοποίηση της ωφέλειας/ κέρδους τους, ή ως μια μη ορθολογική συμπεριφορά και επικεντρώνονται κυρίως στα ψυχολογικά αίτια που οδηγούν τους επενδυτές στην επίδειξη μιας τέτοιας συμπεριφοράς. Με τη παρούσα εργασία προσπαθούμε να καλύψουμε ένα κενό στην υπάρχουσα βιβλιογραφία, καθώς η πλειονότητα των ερευνών έχει μελετήσει αυτό το φαινόμενο στην χρηματιστηριακή αγορά μετοχών και σε μεσοπρόθεσμα διαστήματα προσεγγίζοντας έμμεσα τις συναλλαγές των επενδυτών μέσω των μεταβολών των θέσεων τους στο εξεταζόμενο διάστημα. Ουσιαστικά, η δική μας συμβολή έγκειται στο γεγονός ότι το εξετάζουμε στην αγορά των αμερικάνικων εταιρικών ομολόγων αξιοποιώντας ημερήσια δεδομένα πραγματικών συναλλαγών που έχουν αντληθεί απευθείας από την πλατφόρμα TRACE.

Η αγορά εταιρικών ομολόγων που εξετάζουμε αποτελεί μια εγγενώς αδιαφανή αγορά με έντονα θέματα ρευστότητας σχετικά με τη δημοσιοποίηση πληροφοριών πριν από την εκτέλεση των συναλλαγών, γεγονός που μπορεί να οδηγήσει σε εμφάνιση φαινομένων όπως η αγελαία συμπεριφορά. Επίσης, λόγω του καθεστώτος μηδενικών επιτοκίων, έχει προσελκύσει το ενδιαφέρον των επενδυτών σημειώνοντας μια αύξηση των νέων εκδόσεων της τάξεως των $300τρις τη τελευταία δεκαετία. Ταυτόχρονα επηρεάστηκε έντονα από τις νέες νομοθεσίες που ακολούθησαν τη χρηματοοικονομική κρίση οδηγώντας πολλούς dealers να αποχωρήσουν από την αγορά, χαρακτηριστικά μόνο τη πενταετία 2007-2012 το καθαρό απόθεμα διακρατούμενο από dealers μειώθηκε κατά $170τρις.

Υπό αυτό το πρίσμα μπορεί να θεωρηθεί ιδανική μελέτη περίπτωσης για την εξέτασή του φαινομένου της αγελαίας συμπεριφοράς. Γι' αυτό το λόγο αξιοποιούμε μια πλούσια βάση δεδομένων που αναφέρεται σε αθροιστικές ημερήσιες συναλλαγές για να εφαρμόσουμε μια μεθοδολογία βασισμένη στη μεθοδολογία που προτάθηκε από τον Sias (2004), προσαρμοσμένη όμως στο να εκμεταλλεύεται το γεγονός ότι τα δεδομένα μας έχουν πάνελ μορφή.

Τα κύρια ερωτήματα που επιχειρούμε να απαντήσουμε είναι: Πρώτον, αν συναντάται το φαινόμενο της αγελαίας συμπεριφοράς στην αγορά εταιρικών ομολόγων της Αμερικής σε βραχυπρόθεσμο ορίζοντα. Δεύτερον, αν αυτή η συμπεριφορά είναι γνώρισμα κάποιας ομάδας επενδυτών, δηλαδή εάν οι θεσμικοί ή λιανικοί επενδυτές επιδίδονται σε τέτοιες συμπεριφορές. Τέλος, επιχειρούμε να εντοπίσουμε κάποιους προσδιοριστικούς παράγοντες αυτής της συμπεριφοράς.

Τα κύρια ευρήματά μας επιβεβαιώνουν την ύπαρξη αγελαίας συμπεριφοράς στην αγορά εταιρικών ομολόγων της Αμερικής σε βραχυπρόθεσμο ορίζοντα. Αυτή η συμπεριφορά εμφανίζεται ακόμα πιο έντονη από πλευράς λιανικών επενδυτών. Επίσης, μέσω της ανάλυσης μας τονίζεται η αναποτελεσματικότητα της συγκεκριμένης αγοράς να παράσχει ρευστότητα, ώστε να καλύψει τις συναλλαγές ακόμα και των λιανικών επενδυτών.
Τα αποτελέσματα μας σχετικά με τους θεσμικούς επενδυτές αναδεικνύουν μια τάση των θεσμικών επενδυτών να εμφανίζουν υψηλότερα επίπεδα herding σε μεσοπρόθεσμα ομόλογα και σε ομόλογα που ανήκουν στον χρηματοοικονομικό κλάδο. Ταυτόχρονα βλέπουμε η συμπεριφορά τους να μη διαφοροποιείται ανάλογα με τη πιστοληπτική διαβάθμιση του ομολόγου στα επενδυτικού τύπου ομόλογα.

Όσον αφορά τους λιανικούς επενδυτές, παρατηρούμε να εμφανίζουν αυξανόμενα επίπεδα herding σε ομόλογα με μεγαλύτερη διάρκεια μέχρι τη λήξη όπως και σε ομόλογα του χρηματοοικονομικού κλάδου. Σε αντίθεση με τους θεσμικούς, οι λιανικοί επενδυτές εμφανίζουν υψηλότερα επίπεδα αγελαίας συμπεριφοράς σε ομόλογα χαμηλότερης πιστοληπτικής διαβάθμισης.

Καταλήγοντας, παρατηρούμε ότι από κοινού θεσμικοί και λιανικοί επενδυτές επεκτείνουν τη μιμητική τους συμπεριφορά σε επίπεδο εκδότη, δηλαδή αγοράζουν(πουλάνε) ομόλογα εκδοτών που τη προηγούμενη μέρα ήταν αγορασμένα (πουλημένα). Αξιοσημείωτο είναι το γεγονός ότι οι λιανικοί επενδυτές εμφανίζουν παρόμοια επίπεδα αγελαίας συμπεριφοράς τόσο στην εξέταση των μεμονωμένων τίτλων όσο και σε επίπεδο εκδότη.