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

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"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)."

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Extended Summary in Greek- Ευρεία Περίληψη στα Ελληνικά

Η παρούσα εργασία εξετάζει το φαινόμενο της αγελαίας συμπεριφοράς των θεσμικών επενδυτών στην δευτερογενή εξω-χρηματιστηριακή αγορά εταιρικών ομολόγων της Αμερικής. Με τον όρο αγελαία συμπεριφορά αναφερόμαστε στη τάση των θεσμικών επενδυτών να ακολουθεί ο ένας τον άλλον στην αγορά ή πώληση των ίδιων τίτλων στις καθημερινές τους συναλλαγές, με αποτέλεσμα να διαφαίνεται ένα μιμητικό φαινόμενο όπως αυτό της αγέλης.

Η βιβλιογραφία στο συγκεκριμένο θέμα είναι πλούσια, έχοντας προτείνει πληθώρα μέτρων για τη μέτρηση αυτής της τάσης καθώς και πολλές θεωρίες για την εξήγησή της. Θα μπορούσαμε να διακρίνουμε τις θεωρίες αυτές σε δύο κατηγορίες, αυτές που χαρακτηρίζουν την αγελαία συμπεριφορά ως μια ορθολογική συμπεριφορά των επενδυτών και σε αυτές που την κατατάσσουν στις μη ορθολογικές συμπεριφορές. Η πρώτη κατηγορία θεωριών προσεγγίζει την αγελαία συμπεριφορά ως μια εξωτερικότητα της διαδικασίας μεγιστοποίησης του κέρδους (ακριβέστερα, ελαχιστοποίησης του κόστους) από πλευράς των επενδυτών. Η δεύτερη κατηγορία επικεντρώνεται κυρίως στα ψυχολογικά αίτια που οδηγούν τους επενδυτές στην επίδειξη μιας τέτοιας συμπεριφοράς. Καθώς ο κύριος όγκος των υπαρχουσών ερευνών εστιάζει στην μελέτη του φαινόμενου στην αγορά μετοχών, σε μεσοπρόθεσμα διαστήματα (3-6 μηνών) χρησιμοποιώντας προσεγγίσεις των επενδυτικών συναλλαγών, η εργασία μας επιχειρεί να καλύψει το κενό αυτό εξετάζοντας την αγορά αμερικάνικων εταιρικών ομολόγων σε ημερήσια βάση και αξιοποιώντας δεδομένα πραγματικών συναλλαγών. Επιλέξαμε την αμερικάνικη αγορά εταιρικών ομολόγων καθώς αποτελεί μια δομικά μη ρευστή αγορά και χαρακτηριστικά αδιαφανή, όσον αφορά τη δημόσια πληροφόρηση πριν την εκτέλεση των συναλλαγών, χαρακτηριστικά που δημιουργούν πρόσφορο έδαφος για την εμφάνιση φαινομένων όπως της αγελαίας συμπεριφοράς. Επιπλέον, την τελευταία δεκαετία, λόγω του καθεστώτος μηδενικών επιτοκίων, προσέλκυσε το ενδιαφέρον των επενδυτών σημειώνοντας μια αύξηση νέων εκδόσεων της τάξεως των $300τρις. 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.

Σε αυτό το πλαίσιο αξιοποιούμε μια πλούσια βάση δεδομένων αθροιστικών ημερήσιων συναλλαγών και χρησιμοποιώντας μια μεθοδολογία βασισμένη στη μεθοδολογία που ακολούθησε ο Sias (2004), προσαρμοσμένη όμως στο να εκμεταλλεύεται το γεγονός ότι έχουμε πάνελ δεδομένα, προχωράμε στην εξέταση του συγκεκριμένου φαινομένου. Τα δύο καίρια ερωτήματα που απαντάμε είναι πρώτον αν οι θεσμικοί επενδυτές τείνουν να μιμούνται τις συναλλαγές της προηγούμενης ημέρας , δηλαδή αν οι θεσμικοί επενδυτές "ακολουθούν την αγέλη". Δεύτερον επιχειρούμε να αναγνωρίσουμε κάποιους προσδιοριστικούς παράγοντες που εντείνουν αυτή τη συμπεριφορά.

Τα κύρια ευρήματα μας συνηγορούν στο γεγονός ότι υπάρχει μια τάση εκ μέρους των θεσμικών επενδυτών να συγκεντρώνονται γύρω από συγκεκριμένους τίτλους, παρέχοντας έτσι ρευστότητα μόνο σε συγκεκριμένους τίτλους. Χαρακτηριστικά, το δείγμα μας αποτελείται από περίπου 4,000 μοναδικούς κωδικούς ομολόγων (CUSIPs), όμως μόνο οι μισοί είναι κατά μέσο όρο ενεργά διαπραγματεύσιμοι την ημέρα. Σε αυτούς τους τίτλους είναι που παρατηρούμε την πιο έντονη τάση μιμητισμού των συναλλαγών της προηγούμενης μέρας. Συγκεκριμένα, παρατηρούμε μια τάση των θεσμικών επενδυτών να ακολουθούν τις συναλλαγές της προηγούμενης μέρας των ίδιων ή άλλων θεσμικών επενδυτών, καθώς και σε χαμηλότερο βαθμό λιανικών επενδυτών. Η συμπεριφορά αυτή φαίνεται να επεκτείνεται και στα αθροιστικά ανά εκδότη ομολόγου δεδομένα. Επιπλέον, η ανάλυσή μας έδειξε ότι το φαινόμενο της αγελαίας συμπεριφοράς εμφανίζεται πιο έντονο στα ομόλογα χαμηλότερης πιστοληπτικής διαβάθμισης, καθώς και στα μεσοπρόθεσμα ομόλογα (5-15 χρόνια μέχρι τη λήξη). Επίσης, εξετάσαμε στα ομόλογα ποιων κλάδων εμφανίζεται και κατά πόσο διαφέρει ο βαθμός της αγελαίας συμπεριφοράς. Ενδεικτικά τα υψηλότερα επίπεδα εμφανίζει ο κλάδος των Τηλεπικοινωνιών, ακολουθεί ο Βιομηχανικός κλάδος, έπεται ο Τραπεζικός και λοιποί κλάδοι. Τέλος, παρατηρήσαμε υψηλότερα επίπεδα αγελαίας συμπεριφοράς σε ομόλογα που είχαν υπερτιμηθεί ή υποτιμηθεί την προηγούμενη μέρα, που όμως αντιστρέφονται όταν τα ομόλογα αυτά φτάνουν σε ακραία επίπεδα υποτίμησης. Η ίδια διορθωτική συμπεριφορά δεν παρατηρείτε στα ακραία υπερτιμημένα ομόλογα.

Introduction

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 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 regard, this dissertation investigates institutional investors' herding behavior in the U.S. corporate bond market by utilizing a comprehensive dataset from TRACE platform. As herding behavior, we define the tendency of institutional investors to follow each other into or out of the same bonds. In particular, we attempt to recognize micro-structure/ daily patterns in corporate bond market by directly examining the cross-sectional temporal dependence on institutional investors' daily demand. The key empirical questions that we address are:

- Do institutional investors herd in the corporate bond market?
- Which are the main determinants of institutional investors' herding behavior?

Our main results are as follows:

- We document a tendency of institutional investors to concentrate around the same bonds.
- We provide evidence in support of existence of institutional herding behavior on daily basis, particularly at more liquid bonds.
- We reveal a more intense level of institutional herding on lower credit rated and mid-term bonds.
- We point out to sectors in which institutional investors do herd.
- We document a tendency of institutional investors to herd on overvalued and undervalued bonds by following the flow as well as a correction tendency concerning extremely undervalued bonds.

- Lastly, we show that institutional investors herding behavior is expanded at issuer 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.

Theories of Herding

There is a rich theoretical literature suggesting explanations for herding by investors. Under the assumption of asymmetric information there are theories which stipulate that the cost of gathering information, such as time, effort, and financial cost, make herding prudent and even rational for the market participants. In this case, investors glean information more expensively, therefore they base their decisions on the actions of the crowd who assume that knows more than they individually do. Moreover, retail investors are expected to expose themselves to greater tendency to herd on institutional investors, since the latter have access to better information and superior methods of finding information. In other words, those theories suggest that there are cases which are cost efficient for investors to imitate their better-informed colleagues.

There are also approaches that differ from the previous and suggest that herding behavior is more likely to be presented among institutional investors. One of these stipulates that institutional investors such as financial institutions or intermediates, are obliged by the law to dissemble information regarding their portfolios, consequently their investment positions are more readily perceived by their colleagues. On the other hand, retail investors are not forced to disclose their positions, hence it is more difficult to be observed the structure and moves of their portfolios from other investors. A second approach advocates that some institutional investors such as fund managers are evaluated in comparison to the performance of other capital administrators. In this sense, fund managers prefer to keep up with the crowd than walking alone, since if their expectation is not realized, they will have to take on the responsibility by themselves.

The rational model approaches herding as an externality of investors' profit making/maximizing utility process, when the decision process is distorted by difficulties in finding information. As far as the behavioral aspect model (irrational herding) is concerned, this asserts that decision makers may be bound by endogenous and exogenous constraints including the investor's psychology.

Many theories have been proposed across the literature to explain rational and irrational herding by investors. Bikhchandani and Sharma, (2001) divide the herding behavior into “rational” (intentional) herding, where investors have an intention to follow the behavior of others, and “spurious” (unintentional) herding, where investors face similar fundamental-driven information and hence make identical decisions. The former might be inefficient, and it can lead to systemic risk, excess volatility, and fragile markets whereas the latter may lead to an efficient outcome.

Several potential reasons are associated with rational herding behavior in financial markets. The most significant are informational cascades, investigative herding, compensation structures, and concern for reputation.

Informational cascades can result from the fact that institutions infer information from each other’s trade and therefore mimic the crowd ignoring their own private information. This phenomenon also interprets how such social norms and conventions occur, are maintained, or change over time. For instance, the fact that investors enter the market at a later stage might be a rational choice since they follow the trading behavior of previous investors (that may be of possess private information) disregarding their own private information. Regarding their consequences, informational cascades might jolt over perfectly rational individuals and lead to the creation of bubbles.

A decision model, proposed by Banerjee (1992), suggests that it is rational for decision makers to keep track of the decisions made by previous decision makers since the latter might infer important information related to their own. He shows that the optimizing rules in decision making might be the drivers of 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 obtained from previous decisions ignoring private information (as will latter decision makers). They argue that, unrelated to the social desirability of the outcome, the reasoning might be entirely rational. The informational cascades can interpret conformity and the rapid spread of new behaviors. Lastly, they assert that conformist behaviors might be idiosyncratic and fragile because informational cascades rely on even a small set of informations.

In an attempt to study the relationship between asset prices and herding behavior (that arises when traders follow the trend in past trade), Avery & Zemsky (1998) 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. Yet, more complicated information structures can lead to herding behavior and it is likely to affect asset prices only when the market is uncertain for both and the information of the average trader and the asset value. Additionally, a sufficiently complex information structure can make price bubbles possible.

Cipriani & Guarino, (2005) examine the herding behavior in financial markets. In particular, they show that in a frictionless laboratory market in which subjects are trading for informational reasons, herding behavior rarely arises. Their findings are in line with the theoretical predictions of Avery & Zemsky, (1998). Theoretical evidence, however, do not entirely reflect the behavior observed in the laboratory financial market. In some cases there are informed traders that ignore their own private information and abstain from trading or follow a contrarian strategy.

In turn, investigative herding is a consequence of institutional investors following the same signals. Froot, et al. (1992) argue that if speculators have short horizons, they might herd trying to learn information that other informed investors know. They show the existence of short-term speculators, which indicates an informational inefficiency. However, at the pricing stage the market may be considered efficient and investors may tend to concentrate on one set of information due to poor quality or are not related to fundamentals. Their findings can be explained by positive informational spillovers. More specifically, as more speculators acquire a given piece of information, it will be disseminated in the market and thus it is profitable to acquire this information at an early stage. In this regard, herding equilibria may arise in the sense that traders may focus on different variables at different times.

Maug and Naik (2011) provide another theory of herding based on the compensation contracts offered to the fund managers. They study a model which investigates whether asset allocation decisions taken by fund managers are associated with their compensation schemes. Optimal contracts are derived for delegated portfolio management and they lead to relative performance elements. They conclude that fund managers follow allocations of their benchmark sometimes disregarding their own superior information and deviate from return-maximizing portfolio allocations.

Scharfstein & Stein, (1990) show that herding behavior occurs due to reputational concerns of fund managers or analysts. Reputation or, more broadly, career concerns occur because of uncertainty about the ability or skill of a manager. The basic 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 fog (i.e. the uncertainty regarding the ability of the manager to manage the portfolio). They argue that reputation concerns in labor markets and correlated prediction that leads to the "sharing-the-blame" effect might drive managers to follow each other's decisions, without regard to substantial 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. Thus, manager concern for labor market reputation might lead to rational and intentional herding behavior, i.e. institutional managers choose to act similarly as others because they do not want to risk their reputation by doing trades in the different direction from the herds. In other words, herding may be considered as insurance that the manager will not under perform his peers (Rajan, 2006).

In a theoretical model, Trueman (1994) shows 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. To mimic higher ability and acquire higher compensation, analysts tend to forecast earnings like those previously released by other analysts.

Graham, (1999) argues that analysts are more likely to herd when they are characterized by high reputation or low. Moreover, herding behavior may arise when there is strong public information inconsistent with analyst private information or when private information signals across analysts present positive correlation. His model is examined utilizing a dynamic measure of reputation that is constructed with data from analysts who publish investment newsletters.

Other authors assert that a subgroup of investors is irrational and that their existence may lead to bubble-like phenomena and imitation behavior. Specifically, the behavioral herding is unrelated to fundamentals and refers to random events that make investors more optimistic or pessimistic, thus taking into consideration the corresponding investment decisions.

Keynes, (1936) points out that sociological factors such as social conventions may affect investors and might drive market participants to imitate the actions of others during periods of uncertainty. Furthermore, given asymmetry, information deficiency, and the employment of common heuristic rules, even adepts can resort to herding behavior (Baddeley et al.,2004). Thus, irrational herd behavior might result from constraints and psychological stimuli (e.g. psychological biases and pressure from social circles and/or social conventions).

According to Shleifer and Summers, (1990) investors are divided into two main categories; arbitrageurs and noise traders. Firstly, arbitrageurs- also called "rational speculators"- form fully rational expectations about security returns. Secondly, noise/liquidity traders Black, (1986) are defined as irrational investors who act on noise and whose trading behavior may be subject to systematic biases. Additionally, they suggest that some changes in investor sentiment or changes in investor expectations concerning assets are considered irrational and not verified by fundamentals, e.g. investors' response to pseudo-signals such as advice by "financial gurus".

Moreover, irrational herd behavior includes all the errors which refer to either investor's mental conception or his sentiment. People, due to aversion to their loss or adhesion to reference points, may invest their money e.g. in a loss-making investment product in the hope that they will soon win the "losers". In this way, they act myopically either by errors related to their perception or by greed and selfishness.

In this regard, many economists propose formal models on what extent investor sentiment may affect investor trading behavior and lead to systematic asset mispricings. For example, Daniel, et al. (1998) propose a theory where investors are overconfident regarding 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. In particular, they conclude that overconfidence might result to long-lag autocorrelations, return predictability and excess volatility.

Barberis, et al. (1998) present a "parsimonious model" of investor sentiment that predicts investor overreaction and/or underreaction to information. Under this interpretation, their model predicts an underweighting of informative bad news of a different type that arrives afterwards and the overreaction to a long string of bad earnings news or sales figures. Lastly, their findings are consistent with empirical evidence on the shortcomings of personal judgment under uncertainty.

Hong & Stein, (1999) suggest a model with two types of boundedly rational market participants: "newswatchers" and "momentum traders." In particular, each newswatcher is defined as an agent that perceives some private in-formation, but fails to elicit other newswatchers' information from prices. In this study, short-run price underreaction is due to slowly diffusing information about future fundamentals. Momentum traders exploit this slow information dissemination which, in turn, leads to long-term overreaction.

Literature Review

Lakonishok, et al., (1992; LSV henceforth) employ quarterly ownership of shares data on 769 US tax-exempt equity funds (pension funds) for the period 1985 to 1989. It is essential to note that their paper plays an important for later studies as it introduced the fundamental herding measure. In particular, the LSV measure gauges whether a disproportionate number of money managers are buying (selling) a certain security beyond the market-wide buying (selling) intensity in a given period. They distinguish the trading activity of these money managers between positive-feedback trading and herding. Interestingly, LSV conclude that institutional money managers do not destabilize prices of individual stocks in terms of economically significant level of herding. Moreover, they find weak evidence of imitation behavior in the small stocks and stocks with uncertain cash flows. Lastly, they prove less herding at the industry than in individual stocks.

Grinblatt, et al. (1995; henceforth GTW) utilizing 274 mutual funds' quarterly ownership data on portfolio changes from 1974 through 1984. More specifically, their study examines whether mutual funds purchase stocks based on their past returns and simultaneously why they have a tendency to display herding behavior. GTW conclude to similar levels of herding as found by LSV (1992). Regarding momentum trading, they find strong evidence that herding can arise by investors in buying stocks that were past winners than investors selling past losers. In this regard, herding that occurs on the sell side, although positive, seems to be irrelevant to past returns. To examine for significant heterogeneity in the mutual funds, they divide funds regarding to their investment purpose; i.e. balanced funds, growth funds, growth-income funds, aggressive growth funds as well as income funds. Their results are coherent with that herding being even weak after examining for objectives.

Christie & Huang, (1995; CH henceforth), propose a different metric that measures investor herding towards the market consensus. Specifically, they utilize daily and monthly returns for the period 1962 to 1988 to gauge the cross-sectional standard deviation of returns, or dispersions. They indicate that during extreme market movements investors might suppress their own beliefs and base their investment decisions only on the market consensus. Therefore, individual returns will not have repelled too far from the market return and thus return dispersions should be low. Finally, when stocks sensitivity towards the market differs from rational asset pricing suggests that dispersions may increase.

Wermers, (1999) studies the herding behavior to date utilizing mutual funds' quarterly holdings data for the period 1975 through 1994. Following LSV approach, he finds weak level of herding in trades by the funds taking place in an average stock. Furthermore, he shows high level of herding in small stocks. Yet, small stocks do not constitute 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. In contrast to GTW (1995), he finds that herding on the buy-side seems to be more prevalent in high past-return stocks, whereas herding on the sell-side might occur in low past-return stocks and at the same time is irrelevant to window-dressing strategies.

Furthermore, Wermers examines the difference between contemporaneous returns and future stock returns (i.e. returns after 6 months on the stock bought by the herds regarding the stocks sold by the herd). He finds that herding is considered a rational choice and simultaneously can contribute bring about incorporation of news into securities prices. His last finding is consistent with the fact that continuing price trends may also mean that, as institutional investors exhibit herding 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.

Chang et al. (2000, CCK henceforth) investigate the investment behavior of market participants within different international markets. To capture any possible non-linearity between market return and the asset return dispersions, they suggest a test of herding behavior. Their findings indicate the presence of herding for South Korea and Taiwan and the absence of herding in the US and Hong Kong, partial herding in Japan. They also find that for the markets which exhibit herding there is information related to macroeconomic fundamentals (rather than information at the firm level) that affects investor behavior.

Sias, (2004) utilizing the total number of institutional investors required to file 13F reports for the period 1983 to 1997 examines whether and to which extent institutional investors exhibit herding behavior. Applying a new approach, he shows that institutional demand in a given quarter can be related to either herding in others' trades or herding in their own past trades. Specifically, the results are in line with the fact that institutions accumulate and liquidate positions over time to reduce trading costs. Additionally, he indicates that institutional investors herd as a result of following information revealed from each other's trades and that, as trading by institutions is strongly related to contemporaneous returns. In other words, institutional herding is initially correlated with the manner information diffuses, as the positive relation between trading by institutional investors and contemporaneous returns stems from the information included in their activities.

Choi & Sias, (2009) using quarterly data from 1983 to 2005 examine the existence of institutional industry herding in U.S. market. Specifically, they show that the fraction of institutional traders buying an industry the previous quarter is correlated with the fraction buying this quarter, i.e. institutional investors follow each other into and out of the same industries. As far as reputational herding is concerned, they find that institutional industry herding can occur from managers' decisions rather than underlying investors' flows. It is also more prevailing in smaller and more volatile industries and simultaneously is unrelated to institutional industry momentum trading. In addition, herding may lead industry market values away from fundamentals.

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

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

Iihara, et al., (2001) analyze the stock returns and yearly change in ownership utilizing aggregate data from 1975 to 1996 as a proxy for investor herding in Japan. Along with individual and institutional investors, they examine the behavior of foreign investors as they may not follow similar trading activity to Japanese investors. They find that individual investors' herding is less prevalent than institutional and foreign investors' herding, as both institutional and foreign investors impact more stock prices. Their findings are also in line with intra-year positive feedback trading by both foreign and institutional investors.

Caparrelli, et al. (2004) utilizing data for the period of 1988-2001 evaluate herding effects in the capital markets and specifically in the Italian Stock Exchange. They show that herding might arise during periods of great stock levels and sustained growth rate, consistent with Christie and Huang (1995). Moreover, their results imply that herding is greater for large-cap companies lower than for small-caps, and tends to decrease constantly.

Bowe and Domuta (2004) utilize daily data from the Jakarta Stock Exchange and examine whether there is evidence of herding and positive feedback trading on investment patterns of domestic and foreign investors over the examined period of 1997 Asian crisis (January 1997 to December 1999). They show that during the crisis both investor categories exhibit herding behavior with herding on foreign level greater than domestic herding. Moreover, they provide no evidence of positive feedback trading among investor categories or at the individual stock level. In general, their findings indicate that investors' herding behavior does not destabilize the market.

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

Hwang and Salmon (2004) employ daily data from 1993 to 2002 to investigate herding in the US and South Korean stock markets. They proposed a new measure which conditions automatically on fundamentals. Not only can the new approach measure herding towards other factors, but also is able to account automatically for the influence of time series volatility. Given the direction of the market as expressed in return volatility and the level of the mean return, they find significant movements and persistence of herding in both U.S. and South Korean equity markets. Lastly, their findings suggest that herding may arise towards the market portfolio in both bull and bear markets.

Wylie (2005) employing a dataset of the portfolio holdings of 268 U.K. equity mutual funds, received by semiannual reports to investors from 1986 to 1993 tests for herding among U.K. mutual fund managers. He finds that the herding measure increases in the number of managers trading a stock over a period and is higher only for extreme capitalization individual stocks. On the other hand, weak level of herding is observed for stocks aggregated at the industry level or other capitalizations.

To test market wide and industry sector herding, Henker et al. (2006) utilize high frequency intraday data on Australian equities for the year 2001-2002. They provide no evidence of intraday herding and find that that information is disseminated efficiently among participants in the Australian equity market. Their findings also imply that investors in the Australian equity market have a great level of firm specific information and discriminate between securities as predicted by the rational asset-pricing paradigm.

Walter and Weber (2006) examine whether and to which extent German mutual fund managers exhibit herding behavior in German mutual fund industry. They employ the trading activity of 60 German mutual funds over the period 1998 to 2002 and find evidence of herding and positive feedback trading by German mutual fund managers. They conclude that highest sell-side herding might arise during the crash periods, whereas the highest level of buy-side herding may occur during the boom periods. Lastly, they note that a significant portion of herding might can be attributed to spurious herding because of changes in benchmark index composition.

Tan et al. (2008) examine dual-listed A-share and B-share stocks in Chinese market. They utilize data on stock prices, earnings per share, and trading volume for 87 dual-listed firms on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) over the period from 1994 to 2003. They find evidence of herd behavior within both the Shanghai and Shenzhen A-share markets in which domestic individual investors are the main participants, and within both B-share markets, that are dominated by institutional investors. Herding behavior in B-share market is particularly evident under conditions of falling market, whereas herding by A-share investors is more prevalent in rising market conditions.

Employing the same approach with CSAD, Economou et al. (2011) examine whether herding behavior takes place in the Portuguese, Italian, Spanish and Greek market. They construct a survivor-bias-free dataset contained of daily returns for all stocks listed in these four markets from 1998 to 2008. They find that during the recent financial crisis of 2007-2008 intense herding behavior is not observed in any of the four markets considered.

Holmes et al. (2013) using monthly institutional holdings data for the Portuguese stock market from 1998 through 2005 find clear evidence of herd behavior. They analyze institutional herding under different market conditions and conclude that it is intentional rather than spurious. The multivariate analysis also suggests that herding is more prevalent when the market declines or market returns are low. In addition, their results are in line with the view that informational cascades and and/or reputational reasons might be associated with such observed behavior.

To test herd behavior toward consensus Galariotis et al. (2015) utilize daily prices for all US and UK constituent stocks for the period of 1989 to 2011. Applying CSAD methodology, they find that the release of macro information is attributed to the tendency of US investors to herd toward consensus. The announcement of major macroeconomic information may lead to spurious herd behavior regardless of investment style. They also show that in the US herding is owing to both fundamentals and non-fundamentals during different crises (during the Asian and Russian crisis and during the Subprime respectively), whereas UK investors herd due to fundamentals and only during the Dotcom bubble burst.

Employing daily individual and institutional trading data, Li et al. (2017) investigate the differences between individual and institutional investors' herding in Chinese market. They find that well-informed institutional investors herd more intensively than individual ones, as they trade more selectively across different stocks. Interestingly, individual investors' herding behavior is dependent on public information as well as attention-grabbing events. Moreover, their findings suggest that institutional investors act asymmetrically to upgrades and downgrades of market.

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

Nevertheless micro-structure of equity markets is a thoroughly researched issue, bond markets only recently started attracting attention of academic researchers. It is although a fact that corporate bond market are considered crucial market, as they provide an important source of capital for issuers and a significant range of securities for investors. As shown in Table 1, the market size of U.S. corporate bond market is nearly USD 8tr. half of the U.S. equity market. On the contrary, there are 66,000 securities, 8 times more than equity market.

Over last decade, due to zero interest rate Federal Reserve policy, the corporate bond market garnered interest of investors, recording a significant expansion of new issuances. Characteristically, the net corporate bond issuance by nonfinancial firms at the end of 2007 is estimated at $100bn, whereas at the end of 2016 exceeds USD 400bn[1]. (Revising market liquidity).

Additionally, following financial crisis of 2007, many regulations have been implemented to banks in order to enhance the stability of financial system. Among them the Volcker Rule in mid-2012 and later the Basel 2.5 and 3, the main point of which was to increase banks' capital and liquidity requirements. These regulations led a number of banks to announce closures of their proprietary trading operations (i.e. J.P. Morgan and Goldman Sachs-September 2010, Morgan Stanley-January 2011, Bank of America- June 2011, Citigroup- January 2012[2]). As a result of financial crisis and the regulation reforms, the corporate bond market faced a dramatic sell-off on bond inventory held by primary dealers, approximately 80% between 2007 and 2012. Both the increase of outstanding securities and the decrease of dealer's

[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;

inventory asserted concerns in relation to potential liquidity problems in corporate bond market. However, it is estimated that the turnover of corporate bond market did not decelerate as much as it was expected. According to a Market Insight of McKinsey & Company and Greenwich Associates of August 2013, there were actions that dealers get to cut inventories that hurt liquidity; yet in a way, they were balanced by the increase of the velocity of the remaining dealers' inventory turnover. Ultimately, the studies, which were conducted since then, were not conclusive. 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 attributed to the availability of quality intraday trade, quote, and/or order data ("tick" data) to empirical researchers. In this regard, the corporate bond market is not particularly transparent and remains obsolete in comparison to equity market. Corporate bond markets are relatively non-automated, not integrated and are characterized by opacity and illiquidity. Aiming to increase transparency in the corporate bond market, the National Association of Securities Dealers[4] (NASD) initiated on July 1st, 2002 a system known as the Trade Reporting and Compliance Engine (TRACE). TRACE constitutes a transaction reporting and dissemination system for all OTC trades. In particular, dealers are obliged to report their secondary market corporate bond trades through TRACE system within a quarter minute lag of trade execution. In turn, each reported trade 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). Among TRACE data accessible to the public are also the size, price, and time of all corporate bond trades in the US.

However, corporate bond market still remains a predominant dealer driven market with public transactions reporting only for executed trades and quotations accessible

[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.

to a few market specialists. Furthermore market is inherently illiquid with 45k trades per day, which corresponds to the 10.8% of outstanding securities. On the contrary equity market has approximately 40m trades, which corresponds to the 99.7% of outstanding securities. The daily dollar liquidity for corporate bond market averages USD 27.5bn in contrast to equity market where is estimated at USD 282.5bn. In corporate bond market we observe an intense activity in securities after their issuance and following that this activity drops dramatically or ceases. In general, few securities show daily activity making it difficult to study the market in question.

As mentioned above, corporate bond markets are relatively opaque regarding the pre-trade available information and quotation. As far as the sell-side is concerned, there is lack of available information for Dealers to make the market, since 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 due to the fact that wholesale trading happens entirely apart from retail trading creating two different markets for institutional and retail investors respectively. Consequently, retail investors are subject to higher prices than institutional ones (e.g. institutional investors pay on average about 5bps less than retailers[5]). Furthermore, 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 are have been reluctant to take large positions since TRACE reveals their positions and their private information to the public.

In an effort to enhance the pre-trade transparency, liquidity and cost efficiency of the bond markets, regulations have been implemented to establish e-trading in bond market. A consequence of relative growth in electronic trading in the corporate bond markets is that transaction costs per bond faced a decrease related to trade size and an increase concerning credit risk[6]. Yet, it is widely accepted that, due to the structural fragmentations of bond market, the transition to electronic era will be slow to arrive.

[5] Tracing the Bond Market ,2016, KCG Market Insight
[6] Ciampi and Zitzewitz (2010), Adrian, Fleming, Shachar, and Vogt (2015)

In 2013 only 20%[7] of corporate bond activity has mitigated to ATFs (Alternative Trading Systems), which in turn get through dealers.

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.

[7] Corporate Bond E-Trading: Same Game, New Playing Field, 2013, McKinsey&Company and Greenwich Associates Report

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.

In Table (5) we display some descriptive statistics regarding daily trades. As shown in Panel (A), the average number of daily trades is 4.92 and mean traded volume per bond is $2,836,619. The daily volume per bond that came from small, medium and large size trades are on average $131,113, $2,048,131 and $1,638,002 respectively. Furthermore, we observe that on average there are 592 traded issuers with 3.66 active bonds per day.

Finally, we divide our observations into three categories according to the size of total traded volume, less than 100K, between 100K & 1m and more than 1m. In Table (6), we present the joint allocation of daily aggregate buy and sell volumes and trades to each three categories.

Formation of variables

In this section, it is necessary to incorporate a series of variables to continue our analysis. Firstly, we distinguish which trades could be attributed to retail and institutional investors respectively by taking advantage of the fact that our sample contains volume information for the individual size of trades. As retail investors we define small banks, corporations and retailers, whereas as institutional investors we define larger banks and funds. Next, 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 this sense, we define the daily fraction of institutional investors' volume of bond i on day t to the total traded volume by institutional investors on day t, which presents the daily market share of institutional investors on bond i (henceforth market share of institutionals). That is,

$$InstitutionalsShare_{i,t} = \frac{institutional\ volume_{i,t}}{\sum_{t=1}^{T} institutional\ volume_{i,t}}$$

Similarly, we calculate the fraction of retail investors' volume of bond i on day t to the total traded volume by retail investors on day t, which presents the daily market share of retail investors on bond i (henceforth market share of retailers). That is,

$$RetailersShare_{i,t} = \frac{retail\ volume_{i,t}}{\sum_{t=1}^{T} retail\ volume_{i,t}}$$

Given that our variables present the total traded volume by each investor category regardless to the direction of them trades, we recalculate the respective variables incorporating the direction of the aggregate daily trades in term of traded volume. To do so, we firstly calculate the fraction of buying volume of bond i on day t to the total traded volume (i.e. dealer's sell and buy volume) of bond i on day t. That is,

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

Next, we also calculate the daily average buying volume fraction as shown below.

$$E_t(BVfr_{i,t}) = \frac{\sum_{i=1}^{I_t} BVfr_{i,t}}{I_t}$$

Where I_t is the number of actively traded bond on day t.

By employing the above variables, we now generate the signed market share of institutionals and retailers of bond i on day t, as follows.

$$SInstitutionalsShare_{i,t} = \begin{cases} InstitutionalsShare_{i,t} & if \quad BVfr_{i,t} \geq E_t(BVfr_{i,t}) \\ -InstitutionalsShare_{i,t} & if \quad BVfr_{i,t} < E_t(BVfr_{i,t}) \end{cases}$$

And

$$SRetailersShare_{i,t} = \begin{cases} RetailersShare_{i,t} & if \quad BVfr_{i,t} \geq E_t(BVfr_{i,t}) \\ -RetailersShare_{i,t} & if \quad BVfr_{i,t} < E_t(BVfr_{i,t}) \end{cases}$$

It is essential to note that we determine as bought the bonds which their buying volume fraction exceeds or equals to market average. Correspondingly, as sold are defined the bonds which their buying volume fraction falls behind market average.

Correspondingly, we calculate the signed market share of institutionals and retailers of issuer j on day t, as follows.

1. $InstitutionalsShare_{j,t} = \frac{\sum_{i=1}^{I_{j,t}} institutional\ volume_{i,t}}{\sum_{t=1}^{T} institutional\ volume_{i,t}}$

2. $RetailersShare_{j,t} = \frac{\sum_{i=1}^{I_{j,t}} retail\ volume_{i,t}}{\sum_{t=1}^{T} retail\ volume_{i,t}}$

3. $BVfr_{j,t} = \frac{\sum_{i=1}^{I_{j,t}} \$Buy_{i,t}}{\sum_{i=1}^{I_{j,t}} \$Buy_{i,t} + \$Sell_{i,t}}$

4. $E_t(BVfr_{j,t}) = \frac{\sum_{j=1}^{J_t} BVfr_{j,t}}{J_t}$

5. $SInstitutionalsShare_{j,t} = \begin{cases} InstitutionalsShare_{j,t} & if \quad BVfr_{j,t} \geq E_t(BVfr_{j,t}) \\ -InstitutionalsShare_{j,t} & if \quad BVfr_{j,t} < E_t(BVfr_{j,t}) \end{cases}$

6. $SRetailersShare_{j,t} = \begin{cases} RetailersShare_{j,t} & if \quad BVfr_{j,t} \geq E_t(BVfr_{j,t}) \\ -RetailersShare_{j,t} & if \quad BVfr_{j,t} < E_t(BVfr_{j,t}) \end{cases}$

Descriptive statistics of the created variables are provided in Table (7).

Empirical Analysis-Hypothesis Development

In this section, we attempt to pursue patterns related to institutional investors' daily trading activity on corporate bond market. In doing so, we develop our analysis in two stages; during the first stage we test the existence of institutional investors herding behavior in the corporate bond market. In the second stage we analyze the common objectives of institutional investors' herding behavior in the particular market. In this sense, we frame the following eight hypotheses that then we put to test.

<u>Herding Behavior</u>

1: Institutional investors follow other investors on trading the same bonds.

2: Institutional investors follow other investors into or out of the same bonds.

3: Institutional investors exhibit greater level of herding behavior on more liquid bonds.

<u>Determinants of Institutional investors' herding behavior</u>

4: The level of Institutional investors' herding behavior varies among bonds of different credit rating categories.

5: The level of Institutional investors' herding behavior varies among bonds in different maturity bands.

6: The level of Institutional investors' herding behavior varies among bonds of different sectors.

7: Institutional investors herd on bonds' overvaluation/undervaluation.

8: Institutional investors' herding behavior is extended to issuer level.

Empirical Analysis

<u>Hypothesis 1: Institutional investors follow other investors on trading the same bonds.</u>

We frame the first hypothesis to explore whether institutional investors follow other investors, institutionals or retailers, on trading the same bonds over successive days.

To test our hypothesis, we adopt a methodology influenced by Sias approach. In particular, we attempt to directly capture the cross-sectional temporal dependence on institutional investors' concentration on bonds over successive days by regressing the daily market share of institutionals on the previous' day market share of institutionals and retailers respectively. That is,

$$InstitutionalsShare_{i,t} = \\ = a + \beta_1 InstitutionalsShare_{i,t-1} + \beta_2 RetailersShare_{i,t-1} + e_{i,t} \quad (1)$$

It is worth to note that we use a pooled panel regression where the observations are clustered by time. In this way, we let our model to obtain cross-sectional effects.

The regression's results are presented in Column (1) of Table (8). We report a strong positive relation between market share of institutionals today and previous day and a lower yet statistically significant relation with market share of retailers, which average 0.40 and 0.08 respectively. Additionally, we report a positive and statistically significant constant which averages 0.0001. In line with our first hypothesis, our results provide evidence that institutional investors follow each other on trading the same bonds on daily basis. Furthermore, institutional investors follow the trades of retail investors as well but in a lower level. Lastly, the positive constant term indicates that institutional investors have a tendency to concentrate around actively traded bonds. This finding is consistent with the spotlight theory which suggests that investors in the corporate bond market tend to concentrate around bonds which for some reason have attracted the market interest.

Hypothesis 2: Institutional investors follow other investors into or out of the same bonds.

Moving forward with our analysis, we frame the second hypothesis to examine whether institutional investors follow other investors, retailers or institutionals, into or out of the same bonds. To do so, we utilize the signed market share of institutional and retail investors and run the below pooled panel regression.

$$SInstitutionalsShare_{i,t} = \\ = a + \beta_1 SInstitutionalsShare_{i,t-1} + \beta_2 SRetailersShare_{i,t-1} + e_{i,t} \quad (2)$$

As shown in Column (2) of Table (8), we report a positive and statistically significant relation between the signed market share of institutional investors today and previous day which averages 0.04. We also report a weaker but statistically significant relation between the signed market share of institutionals today and the previous day signed market share of retailers which averages 0.006. This finding suggests that institutional investors follow investors on trading the same bonds causing the closure of the market for these bonds to be in the same direction with the previous day (i.e. bought or sold). In other words, institutional investors follow both institutional and retail investors into or out of the same bonds, yet retailers at a lower level. Lastly, we report a positive and statistically significant constant (averages 0.00002) which indicates a buy drift on institutional investors' demand. Our results are consistent with institutional herding behavior theory which we expand on short-term basis.

Hypothesis 3: Institutional investors exhibit greater level of herding behavior on more liquid bonds.

As we mentioned above, the corporate bond market is particularly illiquid. To capture the more liquid part of bond market, we analyze the bonds participating in the formation of JULI Index. Although 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). Consequently, 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 persists on liquid bonds. In doing so, we classify all bonds to 5 quintiles according to their total turnover over the examined period. The first quintile consists of the most illiquid bonds (i.e. lowest total turnover), whereas the fifth quintile includes the most liquid (i.e. highest total turnover). Next, we run a pooled panel regression of the daily signed market share of institutionals on its lagged term and on its lagged term coupled with the turnover dummies (except the dummy of the first quintile which is used as basis). That is,

$$
\begin{aligned}
&SInstitutionalsShare_{i,t} = \\
&\quad = a + \beta_1 \, SInstitutionalsShare_{i,t-1} + \\
&\quad + \beta_2 SInstitutionalsShare_{i,t-1} TurnoverQ2_i + \\
&\quad + \beta_3 SInstitutionalsShare_{i,t-1} TurnoverQ3_i + \\
&\quad + \beta_4 SInstitutionalsShare_{i,t-1} TurnoverQ4_i + \\
&\quad + \beta_5 SInstitutionalsShare_{i,t-1} TurnoverQ5_i + e_{i,t} \qquad (3)
\end{aligned}
$$

Our results are presented in Table (9). We observe that the β1 coefficient is statistically insignificant at confidence level 10% whereas as we move towards more liquid quintiles both coefficients and their confidence level increase (β3 0.041 s.l 10%, β4 0.048 s.l. 5% and β5 0.077 s.l. 1%). In this regard, we reject the above statement that the report positive pattern on institutionals demand over successive day could be attributed to liquidity issues of the corporate bond market. Furthermore, we prove our third hypothesis that institutional investors exhibit a greater tendency to follow each other into or out of the same, more liquid, bonds. In the light of this finding we firmly document a tendency of institutional investors to trade in herds on corporate bond market over successive days.

Having documented that institutional investors trade in herds on corporate bonds market over the period investigated, we move forward with our analysis and attempt to access the determinants of such behavior.

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

A question that firstly arises is whether institutional investors' herding behavior varies through bonds of different credit rating status. According to informational cascades theory of herding, we would expect the herding level of institutional investors to be greater on lower rated bonds. In general, lower rated bonds are characterized by greater uncertainty/risk. In this regard, credit rating status could be a driver of herding behavior based on informational cascades theory. On the other hand, investigative theory of herding suggests that institutional investors' herding behavior arises from the fact that institutional investors get positive correlated signals. In this sense, greater level of herding on higher rated bonds would indicate this theory.

To examine which theory better explains the institutional herding behavior on the US market over the examined period, we frame our fourth hypothesis to test whether herding behavior is differentiated between BBB rated bonds and the bonds on the A credit rating class (i.e. A, AA, and AAA rated bonds).

To do so, we generate a dummy variable for BBB credit rated bonds and run a pooled panel regression of the daily signed market share of institutionals on its lagged term and on its lagged term coupled with dummy. That is,

$$\begin{aligned} SInstitutionalsShare_{i,t} &= \\ &= a + \beta_1\, SInstitutionalsShare_{i,t-1} + \\ &+ \beta_4 SInstitutionalsShare_{i,t-1} D_{BBB_{i,t-1}} + e_{i,t} \quad (4) \end{aligned}$$

.

The regression's results are shown in Table (10). Indeed, we observe a statistical significant difference on level of herding based on credit rating. For the bonds of A credit rating class we report an on average 0.026 level of herding whereas for BBB rated bonds herding level is increased by 0.030. In this regard, our results point out the tendency of institutional investors to disregard their own information and follow other investors' trades regarding riskier bonds. This behavior is considered rational when we consider the uncertainty that prevails on financial markets over the examined period.

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 do so, we incorporate two dummy variables representing bonds with at least 5 to 15 years and 15 to 30 years to maturity respectively. Next, we frame our fifth hypothesis to test whether the herding level of institutional investors on bonds with less than five years to maturity differs from bonds on remaining two maturity bands. To test our hypothesis, we run the respective pooled panel regression employing the maturity bands dummies as shown above.

$$\begin{aligned} SInstitutionalsShare_{i,t} &= \\ &= a + \beta_1\, SInstitutionalsShare_{i,t-1} + \\ &+\ \beta_2 SInstitutionalsShare_{i,t-1} rym(5-15)_{i,t-1} + \\ &+ \beta_3 SInstitutionalsShare_{i,t-1} rym(15-30)_{i,t-1} +\ e_{i,t} \quad (5) \end{aligned}$$

Regressions' results are shown in Table (11). Interestingly, we observe that institutional investors' herding levels are greater for mid-term than short-term bonds, whereas long-term bonds show the lowest herding levels. These findings could be driven by the fact that the main participants on mid-term bonds' market are mutual and hedge funds which mark to market their portfolios. On the contrary, the main participants of long-term bonds' market, pension funds, prefer strategies such as buy and hold.

Hypothesis 6: The level of Institutional investors' herding behavior varies among bonds of different sectors.

Another interesting question is whether the level of herding varies among bonds issued by companies of altered sectors. To test this hypothesis, we create fifteen dummy variables for each sector in our sample. Then we run a pooled panel regression of the daily signed market share of institutionals on its lagged term and on its lagged term coupled with several combinations of the sector dummies. To choose the appropriate model we exclude each time the sector dummies which coefficient do not indicate herding behavior (the joint effect of basis sector and dummy sector average to zero). Below we present the final model.

$$
\begin{aligned}
&SInstitutionalsShare_{i,t} = \\
&\quad = a + \beta_1\, SInstitutionalsShare_{i,t-1} + \beta_2 SInstitutionalsShare_{i,t-1} Banks_i + \\
&\quad + \beta_3 SInstitutionalsShare_{i,t-1} BasicIndustries_i + \\
&\quad + \beta_4 SInstitutionalsShare_{i,t-1} CapitalGoods_i + \\
&\quad + \beta_5 SInstitutionalsShare_{i,t-1} Energy_i + \\
&\quad + \beta_6 SInstitutionalsShare_{i,t-1} Insurance_i + \\
&\quad + \beta_7 SInstitutionalsShare_{i,t-1} MediaEntertainment_i + \\
&\quad + \beta_8 SInstitutionalsShare_{i,t-1} Technology_i + \\
&\quad + \beta_9 SInstitutionalsShare_{i,t-1} Telecoms_i + e_{i,t} \quad (6)
\end{aligned}
$$

Regressions' results, presented in Table (12). Indeed, our results suggest that institutional investors exhibit different level of herding based on bonds of different sectors. We report a more severe level of herding on Telecommunication Industry which averages 0.079. Second higher level of herding is observed on bonds of Basic Industries which averages 0.060. In turn, bonds issued by Banks and companies of Energy and Media & Entertainment sector show levels of herding which do not statistically differs and average approximately 0.05. Similarly, bonds issued by companies of Capital Goods, Insurance and Technology sector exhibited same level of herding which averages approximately 0.03. Correspondingly we do not report a tendency of institutional investors to herd on bonds issued by companies in the sector of Consumer Goods, Healthcare & Pharmaceuticals, Property & Real Estate, Retails, Transportation, Utilities and Diversified.

Hypothesis 7: Institutional investors herd on bonds' overvaluation/ undervaluation.

Another potential driver of institutional investors' herding behavior could be the deviation of bonds' prices from their fundamentals. In this sense, we frame our seventh' hypothesis to examine whether institutional investors trade on herds when the implied par equity spread deviates from credit default swap spread. To do so, we divide our daily observations into five quintiles according to their cds bond basis (i.e. par equity spread minus credit default swap spread). In this sense, the fifth quintile refers to most overvalued bonds, whereas the first indicates the most undervalued. Then, we create two dummies which indicate the transition from higher quintiles to first or second quintile respectively. Correspondingly, we create other two dummy variables which capture the transition from lower quintiles to fourth or fifth quintile respectively.

Next, we run a pooled panel regression utilizing the aforementioned dummy variables, as shown below:

$$
\begin{aligned}
SInstitutionalsShare_{i,t} &= \\
&= a + \beta_1\, SInstitutionalsShare_{i,t-1} + \beta_2 SInstitutionalsShare_{i,t-1} UpQ4_{i,t-1} + \\
&+ \beta_3 SInstitutionalsShare_{i,t-1} UpQ5_{i,t-1} + \\
&+ \beta_4 SInstitutionalsShare_{i,t-1} DownQ2_{i,t-1} + \\
&+ \beta_5 SInstitutionalsShare_{i,t-1} DownQ1_{i,t-1} + e_{i,t} \qquad (7)
\end{aligned}
$$

As shown in Table (13), all coefficients are significant at 5% significance level except of the coefficient related to transition to the fifth quintile. Our results document an increased positive relation on institutional investors' demand for bonds that the previous day were either overvalued or undervalued, yet not extremely. Furthermore, we observe that this relation is even more intense on bonds that the previous day were undervalued (beta 1, 2 and 4 coefficients average 0.03, 0.05 and 0.10 respectively). Additionally, we note a negative relation on institutional investors' demand for bonds that the previous day were extremely undervalued (joint effect of beta 1 and 5 coefficients averages -0.07).

These findings suggest that institutional investors follow each other into (out of) the same bonds causing the overvaluation (undervaluation) of those bonds. However, when the bonds are extremely undervalued, institutional investors' trades tend to correct this market inefficiency by taking the counter side. Last but not least, we do not observe any correction tendency on extremely overvalued bonds. This inefficiency might be due to the fact that it is more difficult to arbitrage on an overvalued bond since it is necessary to hold it.

Hypothesis 8: Herding behavior is expanded on issuer level

Finally, it would be interesting to examine whether institutional investors' herding behavior is expanded to issuer level. To do so, we repeat the same analysis utilizing the signed market share of institutionals and retailers of issuer j on day t. That is,

$$SInstitutionalsShare_{j,t} = \\ = a + \beta_1 SInstitutionalsShare_{j,t-1} + \beta_2 SRetailersShare_{j,t-1} + e_{j,t} \quad (8)$$

The regression's results are presented in Table (14). In line with individual bonds' analysis we report a positive and statistically significant at 1% relation between signed market share of institutional investors today and signed market share of both institutionals and retailers the previous day on issuer level. This finding indicates that institutional investors' herding is expanded to issuer level. Interestingly, we observe a higher level of institutional investors' herding on previous day activity of both insitutionals and retailers, which average 0.049 and 0.024 respectively.

Conclusions

To summarize, in this dissertation we work on an issue that recently has attracted the attention of financial community, herding behavior. Many concerns have risen regarding the implication of such behavior on amplifying stability of financial markets. In particular, we investigate whether institutional investors herd on their daily trades (daily trading activity) in U.S. corporate bond market.

We implement a methodology influenced by Sias approach, which allows us to directly capture the cross-sectional temporal dependence on institutional investors' concentration on bonds over successive days. In this regard, we document a great tendency of institutional investors to follow each other on trading the same bonds as well as lower, yet statistically significant, tendency to follow each other into or out of the same bonds.

Furthermore, we point out an increased tendency of institutional investors to herd on BBB credit rated bonds comparing to A or higher credit rated bonds. Our results provide some evidence is in support of informational cascade theory. We also report greater level of herding on mid-term bonds which can be attributed to the fact that the main participants on that market, mutual and hedge funds, mark to market. Moreover, we indicate sectors on which institutional investors exhibit herding behavior over the examined period. Lastly, we document an expansion of institutional herding behavior at issuer level.

Additionally, we provide evidence that institutional investors herd on bonds over/undervaluation buy following the same direction of trades. Yet, at extremely undervalued bond their direction of trade is reversed to correct. We do not observe the same pattern on extremely overvalued bonds, possibly because it is more difficult to speculate in this case as it needs to hold the bond.

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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[8] 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[9]
Tape latency	Up to 15 minutes (1 day for Block trades)	~0.0008 seconds: SIP Up to 10 seconds:TRF[10]
How are they traded	Exchange (~0%) ATS[11] (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

[8] National Market System
[9] Session Initiation Protocol
[10] Trade Reporting Facility
[11] 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%

Table 5

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
Average number of Issuers per day	270	592	54	111	705
Average number of CUSIPs per Issuer	270	3.66	0.15	2.56	3.96

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

Variable	Obs	Mean	Std. Dev.	Min	Max
InstitutionalsShare	585,348	0.03%	0.06%	0.00%	3.57%
SInstitutionalsShare	585,348	0.00%	0.06%	-3.03%	3.57%
RetailersShare	585,348	0.05%	0.11%	0.00%	5.32%
SRetailersShare	585,348	0.01%	0.12%	-3.55%	5.32%

Table8

	$InstitutionalShare_{i,t}$		$SInstitutionalShare_{i,t}$	
$InstitutionalsShare_{i,t-1}$	0.405	***		
	0.00			
$RetailersShare_{i,t-1}$	0.0789	***		
	0.00			
$SInstitutionalsShare_{i,t-1}$			0.0367	***
			0.00	
$SRetailersShare_{i,t-1}$			0.0064	***
			0.00	
Constant	0.0001	***	0.00002	***
	0.00		0.00	
overall Rsq	0.22		0.002	
Number of Obs	456,441		456,441	
Number of Groups	267		267	
Avg Obs per Groups	1,710		1,710	

Table 9

		$SInstitutionalShare_{i,t}$	
$SInstitutionalsShare_{i,t-1}$		-.02750	
		.18700	
$SInstitutionalsShare_{i,t-1}$	$Turnover\_Q2_i$	0.015	
		0.52	
	$Turnover\_Q3_i$	0.041	*
		0.06	
	$Turnover\_Q4_i$	0.048	**
		0.02	
	$Turnover\_Q5_i$	0.077	***
		0.00	
Constant		0.00002	***
		0.00	
overall Rsq		0.002	
Number of Obs		456,441	
Number of Groups		267	
Avg Obs per Groups		1,710	

Table 10

		$SInstitutionalShare_{i,t}$	
$SInstitutionalsShare_{i,t-1}$		.02560	***
		.000	
$SInstitutionalsShare_{i,t-1}$	$BBB_{i,t-1}$	0.030	***
		0.00	
Constant		0.000025	***
		0.00	
overall Rsq		0.002	
Number of Obs		456,441	
Number of Groups		267	
Avg Obs per Groups		1,710	

Table 11

		$SInstitutionalShare_{i,t}$	
$SInstitutionalsShare_{i,t-1}$		.03120	***
		.000	
$SInstitutionalsShare_{i,t-1}$	$Qrym5\text{-}15_{i,t-1}$	0.022	***
		0.00	
	$Qrym15\text{-}30_{i,t-1}$	-0.01	**
		0.02	
Constant		0.000025	***
		0.00	
overall Rsq		0.002	
Number of Obs		456,441	
Number of Groups		267	
Avg Obs per Groups		1,710	

Table 12

		$SInstitutionalShare_{i,t}$
$SInstitutionalsShare_{i,t-1}$		-.00655
		.12100
$SInstitutionalsShare_{i,t-1}$	Banks	0.054 ***
		0.00
	Basic Industries	0.067 ***
		0.00
	Capital Goods	0.026 **
		0.02
	Energy	0.047 ***
		0.00
	Insurance	0.026 **
		0.02
	Media Entermaintment	0.045 ***
		0.00
	Technology	0.039 ***
		0.00
	Telecoms	0.086 ***
		0.00
Constant		0.000025 ***
		0.00
overall Rsq		0.002
Number of Obs		456,441
Number of Groups		267
Avg Obs per Groups		1,710

Table 13

		$SInstitutionalShare_{i,t}$
$SInstitutionalsShare_{i,t-1}$		.03420 ***
		.000
$SInstitutionalsShare_{i,t-1}$	$UpQ4_{i,t-1}$	0.046 **
		0.02
	$UpQ5_{i,t-1}$	-0.040
		0.13
	$DownQ2_{i,t-1}$	0.096 ***
		0.00
	$DownQ1_{i,t-1}$	-0.103 ***
		0.00
Constant		0.000043 ***
		0.00
overall Rsq		0.002
Number of Obs		64,542
Number of Groups		49
Avg Obs per Groups		1,317

Table14

	$SInstitutionalShare_{j,t}$
$SInstitutionalsShare_{j,t-1}$	0.050 ***
	0.00
$SRetailersShare_{j,t-1}$	0.025 ***
	0.00
Constant	-0.00003 ***
	0.05
overall Rsq	0.006
Number of Obs	138,900
Number of Groups	267
Avg Obs per Groups	520