Institutional Herding and Its Price Impact: Evidence from the Corporate Bond Market*

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Abstract

Among growing concerns about potential financial stability risks posed by the asset management industry, herding has been considered as an important risk amplification channel. In this paper, we examine the extent to which institutional investors herd in their trading of U.S. corporate bonds and quantify the price impact of such herding behavior. We find that, relative to what is documented for the equity market, the level of institutional herding is much higher in the corporate bond market, particularly among speculative-grade bonds. In addition, mutual funds have become increasingly likely to herd when they sell, a trend not observed among insurance companies and pension funds. We also show that bond investors herd not only within a quarter, but also over adjacent quarters. Such persistence in trading is largely driven by funds imitating the trading behavior of other funds in the previous quarter. Finally, we find that there is an asymmetry in the price impact of herding. While buy herding is associated with a permanent price impact that is consistent with price discovery, sell herding results in transitory yet significant price distortions. The price destabilizing effect of sell herding is particularly strong for high-yield bonds, small bonds, and illiquid bonds and during the recent global financial crisis.

Keywords: Corporate Bond; Herding; Liquidity; Institutional Investors; Return Reversal

JEL Codes: G01, G02, G12, G14, G20

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1 Introduction

In recent years, regulators, researchers, and market participants have become increasingly concerned about the financial stability risk of institutional investors' herding behavior in trading fixed-income securities (Feroli et al. (2014); FSOC (2015)). An area of particular interest is the market for corporate bonds, where trading liquidity and price discovery rely on liquidity provision by securities dealers (Stein (2014)). Two recent trends have intensified such concerns in this market. On the one hand, the U.S. corporate bond market has expanded rapidly since the crisis, boosted by significant increases in institutional holdings.[1] On the other hand, over the same time period, dealers have sharply shrunk their balance sheets, which may limit their market-making capacity (Levine (2015)).

As such, a surge in simultaneous buying or selling caused by institutional herding could drive asset prices away from their fundamentals, particularly on the downside, and dealers' limited market-making capacity would only exacerbate this price distortion (Duffie (2010)).[2] Such a potential negative price impact could spiral downwards and accelerate redemption from end investors, which amplifies financial stability risks (Chen, Goldstein, and Jiang (2010a); Goldstein, Jiang, and Ng (2015)).[3]

Against this backdrop, we address two key empirical questions in this paper: Do institutional investors herd in the fixed-income markets? If so, does institutional herding destabilize bond prices? In doing so, we fill a gap in the literature on institutional herding, because most

[1] Based on estimates from the Financial Accounts of the United States, the corporate bond market reached \$9.2 trillion as of the end of 2014, about three-quarters of which were held by institutional investors.

[2] Duffie (2010) argues that dealers' balance sheet constraints may prevent capital from moving quickly to profitable opportunities at the time of shocks, resulting in a sharp price reaction and a subsequent reversal. For related empirical evidence, Ambrose, Cai, and Helwege (2012) and Ellul, Jotikasthira, and Lundblad (2011) have mixed results on the price impact of institutional sales in the corporate bond market, and Bao, O'Hara, and Zhou (2016) and Bessembinder et al. (2016) find that dealers' capacity of market-making affects corporate bond trading liquidity.

[3] The negative price impact could imply a first-mover advantage, which may lead to strategic runs, in that fund shareholders want to redeem quickly if they expect that other investors will withdraw their money from the fund and therefore reduce the expected return from staying in the fund. Chen, Goldstein, and Jiang (2010a) find evidence of such strategic, "bank-run" type behavior among corporate bond mutual funds. Goldstein, Jiang, and Ng (2015) find that corporate bond mutual funds' outflows react to bad fund performance more than their inflows to good performance.

of the existing studies have focused on the equity market, where the level of institutional herding is low and evidence on the price impact of herding is mixed.[4] In contrast, we find a high level of institutional herding in the corporate bond market and a strong destabilizing effect of such sell herding.

Taking advantage of a comprehensive data set on U.S. corporate bond holdings by institutional investors, we first estimate the magnitude of institutional herding based on the widely-used measure introduced by Lakonishok, Shleifer, and Vishny (1992) (henceforth "LSV"). We then adopt several strategies to examine the determinants of herding, including panel regressions to assess how institutional herding varies with bond characteristics as well as past bond performance and past herding levels. We also estimate the extent to which herding is driven by mimicking behavior among these investors. Finally, we apply a portfolio approach to analyze the price impact of herding, which also sheds light on the sources of herding. Specifically, if institutional investors herd based on non-fundamental factors such as reputation concerns, we should generally observe bond prices overshoot temporarily and reverse course in the long run (Scharfstein and Stein (1990)). In contrast, if institutional herding is based on bond fundamentals, their collective trades should contribute to price discovery, and there should not be price reversal afterward.

Importantly, we conduct our analysis separately for three types of institutional investors in this market—mutual funds, insurance companies, and pension funds. This helps us understand better the implication of herding because investor behaviors may differ due to their different regulatory, payout, and governance structures. As such, we compare the prevalence of herding behavior and its price impact across these investor types within a unified setting.

Our main results are as follows. First, we find that the level of institutional herding in corporate bonds is substantially higher than what has been documented for equities,

[4]For papers on institutional herding in the equity market, see, for examples, Lakonishok, Shleifer, and Vishny (1992); Froot, Scharfstein, and Stein (1992); Hirshleifer, Subrahmanyam, and Titman (1994); Wermers (1999); Hirshleifer and Hong Teoh (2003); Sias (2004); and Brown, Wei, and Wermers (2013). Earlier papers (Nofsinger and Sias (1999), Wermers (1999) and Sias (2004)) find no evidence of price reversal after herding, but papers that focus on more recent time periods do (Sharma, Easterwood, and Kumar (2006); Brown, Wei, and Wermers (2013); Puckett and Yan (2008); and Dasgupta, Prat, and Verardo (2011)).

particularly so among bonds with lower ratings, and that sell herding is generally stronger than buy herding. Specifically, we estimate that the average bond herding levels of pension funds and mutual funds are each about 10 percent, significantly higher than the levels of about 3 percent for the respective type of equity funds.[5] Intuitively, our estimates indicate that funds in each group are roughly 10 percent more likely to trade on the same side than one would expect if they made their trading decisions independently. Insurance companies, the largest investor group of corporate bonds, have an even greater tendency to herd than mutual funds and pension funds, boasting an average herding level of 13 percent.

Further, we also find that the herding level in trading lower-rated bonds—at 12 and 22 percent for high-yield and unrated bonds, respectively—is notably higher than that for investment-grade bonds, 9 percent. Moreover, we find that sell herding in corporate bonds is significantly stronger than buy herding—a result mostly driven by mutual funds, the most active traders and fastest-growing investors of corporate bonds. Over time, mutual funds also stand out by exhibiting unique trends, with buy herding levels declining and sell herding levels rising.

Second, we find that rating changes, bond liquidity, and past bond performance are key factors that drive herding by different types of investors. All institutional investors are found to herd more in lower-rated and smaller-sized bonds. Perhaps unsurprisingly, insurance companies react more to rating-change events, particularly downgrades, consistent with the fact that they are subject to rating-based regulatory constraints. We find some evidence that mutual funds and pension funds take advantage of such market frictions to buy bonds when insurance companies are forced to sell. We also find that all investors herd to buy winning bonds and herd to sell losing bonds, with insurance companies' herding behavior most sensitive to bonds' past performance.[6]

[5] The average herding levels for equity pension funds (for example, Lakonishok, Shleifer, and Vishny (1992)) and equity mutual funds (for example, Wermers (1999) and Brown, Wei, and Wermers (2013)) have been found in the 2.5–3 range.

[6] This result is consistent with the finding by Becker and Ivashina (2015), who document that conditional on credit ratings, insurance companies' portfolios are systematically biased toward higher yield corporate bonds, a behavior described as "reaching-for-yield."

Interestingly, this herding-to-performance relationship is nonlinear. Specifically, we find that extremely bad past performances are associated with disproportionally large selling herds, while top-performing bonds do not attract disproportionally large buying herds. Such asymmetry suggests that bonds' extremely bad past performances may trigger a larger amount of simultaneous sells from institutional investors, a condition that could lead to further price declines and in turn result in more sells and a downward price spiral. Our nonlinear herding-to-performance results echo previous findings by Goldstein, Jiang, and Ng (2015), who show that bond mutual funds' outflows are more sensitive to bad performance than their inflows to good performance. These results jointly suggest that when bond mutual funds experience outflows because of bad past performance, they are more likely to liquidate the same underperforming bonds at the same time.

Third, we document strong persistence in herding, especially on the sell side. We show that bond investors not only herd within a quarter, but also herd over adjacent quarters. In fact, intertemporal correlation in corporate bond trading is much higher than that in equity trading, especially for insurance companies. Adopting the methodology of Sias (2004), we further decompose intertemporal herding into an imitation component (institutional investors following others into and out of the same securities) and a habit component (investors following their own trades in the last quarter). We find that, strikingly, the positive intertemporal correlation in bond trading is mostly driven by institutions following others' trades. This finding is in stark contrast with those previously documented in equity trading. For example, Sias (2004) finds that for equities the imitation component contributes only about equally as the habit component does to herding persistence. The strong imitation-driven intertemporal herding in corporate bonds implies that herding in this market is more akin to run behaviors than in the equity market.

Finally, and most importantly, we document a significant price-destabilizing effect of sell herding, suggesting that institutional sell herding could pose substantial risks to financial stability. We find that, while buy herding is associated with permanent price impact that facilitates price discovery, sell herding results in transitory yet significant price distortions and therefore excess price volatility. The impact of institutional herding on long-term corporate bond returns is substantial. In particular, when investors herd to sell, bond prices fall substantially during the event period but reverse gradually over the following quarters. A contrarian portfolio that is long in bonds with the highest sell herding measures and short in bonds with the highest buy herding measures generates a cumulative abnormal return of 2.5 percent in six quarters after portfolio formation. Such an abnormal return is entirely driven by subsequent return reversals in bonds that experience heavy sell herding in the event period. This evidence is consistent with what Dasgupta, Prat, and Verardo (2011) and Brown, Wei, and Wermers (2013) find in the equity market, but the impact on bond returns is much stronger in magnitude.

We also find that the price destabilizing effect of sell herding is particularly strong for high-yield bonds, small bonds, and illiquid bonds, and during the recent global financial crisis. Specifically, the contrarian portfolio described above generates a cumulative abnormal return of 6 percent if constructed with high-yield bonds, 4 percent with small bonds, and 5 percent with less-liquid bonds, in six quarters after portfolio formation. If we focus on the 2007-2009 financial crisis period, the price destabilizing effect reaches 8 percent, much greater than that for the full sample period. Our results clearly point to the vulnerabilities associated with institutional sell herding in the corporate bond market, i.e., the price-destabilizing effect is strongest for the most risky bonds during periods of market distress.

Overall, our analysis finds that institutional herding in the U.S. corporate bond market is much stronger than in the equity market, driven by both characteristics-based and mimicking motives. Moreover, while institutional investors herd to buy bonds in a value-discovery manner, their sell herding destabilizes bond prices, particularly so for the riskier bonds during periods of market distress. These findings suggest that institutional sell herding in corporate bonds could pose substantial risks to financial stability. To our knowledge, this is the first paper that documents a price-destabilizing effect of correlated trading by corporate bond investors.

The rest of the paper is organized as follows. Section 2 reviews previous work that is related to this paper. Section 3 describes the data, sampling, and our construction of herding measures; Section 4 assesses the levels, determinants and persistence of herding; Section 5 explores the price dynamics associated with herding; and Section 6 concludes.

2 Related Work

This paper contributes to several strands of literature. First, our empirical results bring a unique quantitative insight to the literature on the nature of herding behavior. Theorists have long been interested in the mechanism of herding behavior and whether it hinders efficiency in the financial market. Roughly speaking, existing models of herding fall into two broad groups, depending on their predictions on price dynamics. In the first group of the models, investors rationally ignore their private information sets and imitate others' behavior. Such herding behavior generally results in market inefficiency and excess price volatility. The underlying mechanism may include information cascades, reputational concern, and benchmark-based compensation structures.[7] In contrast, in the second group of models, investors' trading decisions are driven by fundamentals and their herding behavior results in fast price discovery. These models include investigative herding where a group of asset managers receive similar signals and thus tend to trade on the same side, and characteristics-driven herding where a group of asset managers share common preferences for securities with certain characteristics.[8]

Existing research has well recognized that it is in general very difficult to empirically identify the exact source of the observed herding behavior. See, for example, Bikhchandani

[7] For models of information cascades, see Banerjee (1992); Bikhchandani, Hirshleifer, and Welch (1992); Welch (1992); Avery and Zemsky (1998); Lee (1998); Cipriani and Guarino (2014). For models of reputational concern, see Scharfstein and Stein (1990); Trueman (1994); Graham (1999). For models of benchmark-based compensation structures, see Roll (1992); Maug and Naik (2011).

[8] For models of investigative herding, see Froot, Scharfstein, and Stein (1992); Hirshleifer, Subrahmanyam, and Titman (1994); Devenow and Welch (1996). For models of characteristics-driven herding, see Falkenstein (1996); Del Guercio (1996); Bennett, Sias, and Starks (2003).

and Sharma (2000) for discussions on the challenges. Nonetheless, empirical results on the price impact of herding may help identify the motives along the above dichotomy (Scharfstein and Stein (1990); Brown, Wei, and Wermers (2013)). That is because most imitation herding models predict price distortions and subsequent price reversals.[9] In contrast, fundamental-driven herding tends to aid price discovery and stabilize market.

In this regard, our study suggests that the motives of institutional herding in corporate bond trading may be multifaceted. On the one hand, we find that the price-destabilizing effect of sell herding is consistent with the predictions of herding caused by factors such as information cascades or reputation concerns. On the other hand, we find that buy herding improves price efficiency, consistent broadly with the fundamental-based herding theory.

Second, our paper fills a gap in understanding the potential financial stability risks posed by institutional investors' herding behavior. Earlier studies on the stock market find some evidence that institutional herding tends to move prices toward, rather than away from equilibrium values, possibly because institutions are generally well-informed and so likely herd to undervalued stocks and away from overvalued stocks.[10] However, papers using more recent stock market data find some price-destabilizing effects of institutional herding, especially on the sell side.[11] To the best of our knowledge, our paper is the first to study the price impact of herding in the fixed-income market, and the first to document the asymmetric effects of buy and sell herding on bond prices. In particular, the price-destabilizing effects of sell herding in corporate bonds are much larger in magnitude than what is documented for the stock market. These results not only provide an interesting contrast to those in previous studies on equity markets, but also suggest that the growing concern about financial stability risks associated with institutional herding is warranted in the fixed-income market.

[9] One exception is Khanna and Mathews (2011), who argue that when information production is endogenous, asset managers may have incentives to obtain better information to become leaders of a herd. The improved information production and aggregation may overweigh the herding-induced loss of information efficiency.

[10] See Lakonishok, Shleifer, and Vishny (1992); Froot, Scharfstein, and Stein (1992); Hirshleifer, Subrahmanyam, and Titman (1994); Wermers (1999); and Sias (2004).

[11] See Sharma, Easterwood, and Kumar (2006); Puckett and Yan (2008); Dasgupta, Prat, and Verardo (2011); and Brown, Wei, and Wermers (2013).

Third, we add to the emerging literature on the behavior of corporate bond institutional investors. While institutional investor behavior has been a central topic of the asset management literature, most of the studies focus on equity investors.[12] Recent developments in the fixed-income market have elicited a soaring demand for a better understanding of the behavior of corporate bond investors. Aided with greater availability of data, recent studies have explored a number of aspects of bond investor behavior. For examples, Chen and Qin (2015) and Goldstein, Jiang, and Ng (2015) explore the flow-to-performance patterns of corporate bond mutual funds, Chen, Ferson, and Peters (2010b) evaluate the timing ability of bond funds, Moneta (2015) studies the relationship between bond fund performance and their portfolio holdings, Becker and Ivashina (2015) document a "reaching-for-yield" behavior of insurance companies in their investment on corporate bonds, and Manconi, Massa, and Yasuda (2012), Ellul, Jotikasthira, and Lundblad (2011) and Ambrose, Cai, and Helwege (2012) study the fire-sale behavior of bond mutual fund and insurance companies, respectively. We complement the literature by providing a comprehensive analysis on the correlated trading behavior of three major institutional investors of corporate bonds—mutual funds, insurance companies, and pension funds.

Finally, we contribute to the literature on the role of institutional investors in affecting trading frictions in the corporate bond market. Mahanti et al. (2008) suggest that institutional holding of corporate bonds may serve as a proxy for the bond trading liquidity. Cici, Gibson, and Merrick (2011) and Bessembinder, Maxwell, and Venkataraman (2006) document the transaction costs of mutual funds and insurance companies, respectively, in trading corporate bonds. Manconi, Massa, and Yasuda (2012) investigate the role of institutional investors in transmitting financial shocks. Huang et al. (2013) examine how institutional investors' liquidity preferences interact with bond prices. Our paper sheds light on the relationship between institutional herding and pricing frictions in the corporate bond market, by showing that herding may generate price distortions and market illiquidity may in turn

[12]See, for example, Brown, Harlow, and Starks (1996); Chevalier and Ellison (1997); Coval and Stafford (2007).

promote herding.

3 Data, Sampling, and Herding Measures

3.1 Data and Sampling

We compile our data from multiple sources. We obtain data on institutional investors' holdings of corporate bonds from Thomson Reuters Lipper eMAXX. This database contains quarter-end security-level corporate bond holdings of insurance companies, mutual funds, and pension funds, which we interchangeably refer to as "funds," "investors," or "institutions" throughout the paper.[13] We also use the Fixed Investment Securities Database (FISD) for additional bond and issuer information.

Following the literature, we define "trades" as changes in funds' quarter-end holdings. A limitation for this definition is that quarter-end portfolio snapshots cannot capture intra-quarter round-trip transactions. However, the relatively low frequency of corporate bond trading helps alleviate this issue.

For the purpose of estimating the price impact of herding, we need quarter-end market valuation of corporate bonds. We obtain the bond pricing data from the Bank of America Merrill Lynch's (ML) Corporate Bond Index Database. The ML data contain daily closing bid prices, quoted by major dealers, for a representative pool of U.S. public corporate bonds. This database has several advantages over the transaction data from the Trade Reporting and Compliance Engine (TRACE).[14] Due to the low trading frequency of corporate bonds, using only the quarter-end pricing information from TRACE will result in not only a rather sporadic sample but also a selection bias towards more frequently traded bonds. The ML data, on the other hand, allow for a better-covered and more balanced sample as dealer

[13]To address the potential concern that life insurance companies may behave differently from other insurers (for example, property and casualty insurance companies), we repeat all tests separately for life insurers and non-life insurers, and obtain qualitatively similar results.

[14]In 2002, the Financial Industry Regulatory Authority started to require its member dealers to report their secondary market transactions to TRACE.

quotes are available even when a bond is not traded. Moreover, since the implementation of TRACE, the ML daily price has become essentially the same as the last customer-to-dealer trade price in TRACE whenever there is such a trade during the day.

We construct a "full sample" and a "herding sample," both covering the period from 1998:Q3 to 2014:Q3. Specifically, we restrict our full sample to dollar-denominated, fixed-coupon corporate bonds issued by U.S. companies.[15] We use this full sample to examine the data coverage and overall investor composition.

Based on the full sample, we impose further restrictions to form our "herding sample"—the sample that will be used in our analysis of institutions' herding behavior. Specifically, similar to Wermers (1999), when measuring herding, we exclude bonds that are issued or maturing within one year so as to focus on institutions' "active" trading decisions. Further, we require bonds to be traded by at least five institutional investors in a given quarter.[16]

3.2 Sample Statistics

We first examine our data coverage using the full sample. As shown in Figure 1a, from 1998:Q3 to 2014:Q3, the total number of institutions have increased from about 4,000 to nearly 6,000, driven mainly by the rapid growth in the bond mutual funds (ICI (2016)). We also find that while the total number of bonds in our full sample, shown in Figure 1b, are roughly steady at about 30,000, the dollar value of total holdings , shown in Figure 1c, has risen from $1 trillion to $2.7 trillion. The majority of this increase is recorded in the post-crisis period, consistent with the recent sizable expansion of the corporate bond market.[17] Notably, mutual funds have substantially increased the number of bonds held in their portfolios over time, and their market shares in dollar amount have risen from 19 percent to 34 percent.

[15] Fixed-coupon bonds make up about 95 percent of total observations in the eMAXX data.

[16] For robustness, we repeat all tests related to herding after further requiring bonds to be traded by at least ten institutional investors. The results are qualitatively similar.

[17] Throughout the period, the total dollar amount outstanding of the bonds covered by our data has steadily represented roughly one-third of the U.S. corporate bond universe, based on the bond market size figures reported in the Financial Accounts of the United States.

Table I characterizes institutional holdings and trading activities for three sub-periods—pre-crisis period (1998-2006), crisis period (2007-2010), and post-crisis period (2011-2014). With all investors together, average amount and number of holdings have increased over time, so have the trading activities on both buy and sell sides. In particular, in the post-crisis period, an average institution holds 134 bonds worth $403 million at a quarter-end, buys 21 bonds and sells 20 bonds in a quarter, roughly 9 and 13 of which, respectively, are "active trades"—trades that occur at least one year after issuance and at least one year before maturity. By investor type, mutual funds and pension funds have become significantly more active in trading, while insurance companies' level of activity has remained stable and low. Of note, on average, mutual funds are the most active traders of corporate bonds. To this point, the time series plots in Figure 2 show clearly that mutual funds' total trading frequency and volume have both increased significantly over the sample period.

Table II presents summary statistics of a typical bond in our sample, excluding bonds that are issued or maturing within one year. Overall, the size of an average bond and the number of its institutional holders/traders have increased over time, while the average age (time since issuance) and remaining time to maturity have remained stable. In particular, an average bond held in the 2011–2014 period has an outstanding amount of $662 million—of which $246 million is held by 34 investors in our sample—is about 4 years after issuance, and has 9 years remaining to maturity. On average, it is "actively" sold by 13 institutions and bought by 9 institutions in a quarter. Compared to high-yield bonds, investment-grade bonds tend to have larger size and longer time to maturity, and are more widely held by institutional investors. As for trading intensity, in a typical quarter after 2007, both investment-grade and high-yield bonds are traded more frequently than before.

3.3 Herding Measures

Following the existing literature, we adopt the herding measure proposed by Lakonishok, Shleifer, and Vishny (1992) to estimate the extent of herding by institutional investors in trading corporate bonds. 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 a given period. We estimate the herding measure for each bond-quarter.

Specifically, our herding measure (HM) of bond i in quarter t is defined as

$$HM_{i,t} = |p_{i,t} - \mathrm{E}[p_{i,t}]| - \mathrm{E}|p_{i,t} - \mathrm{E}[p_{i,t}]|, \tag{3.1}$$

where $p_{i,t}$ is the proportion of buyers to all active traders of bond i in quarter t. That is,

$$p_{i,t} = \frac{\#\text{ of Buy}_{i,t}}{\#\text{ of Buy}_{i,t} + \#\text{ of Sell}_{i,t}}. \tag{3.2}$$

The term $\mathrm{E}[p_{i,t}]$ is the expected level of buy intensity. Following previous studies, we estimate $\mathrm{E}[p_{i,t}]$ using the proportion of buyers to active traders of all corporate bonds, that is, the market-wide intensity of buying, during quarter t, or $\overline{p}_t$. That is,

$$\overline{p}_t = \frac{\sum_i \#\text{ of Buy}_{i,t}}{\sum_i \#\text{ of Buy}_{i,t} + \sum_i \#\text{ of Sell}_{i,t}}. \tag{3.3}$$

Therefore, the first term in equation (3.1) measures how much the trading pattern of bond i varies from the general trading pattern of corporate bonds in quarter t, driven by disproportionally buying or selling by the group of investors under consideration. Note that $\overline{p}_t$ varies only over time.

Under the null hypothesis of no herding, all institutional investors make independent trading decisions, and all bonds should have the same probability of being bought (versus sold) in a given quarter.[18] The second term in equation (3.1) is an adjustment factor to account for the fact that the absolute value of $p_{i,t} - \mathrm{E}[p_{i,t}]$ is always greater than zero. The adjustment ensures that under the null hypothesis, the herding measure $HM_{i,t}$ for bond i in quarter t is expected to be zero. Therefore, a positive and significant average herding measure will be evidence for institutional herding in the corporate bond market. Also, herding measures are defined in a way that adjusts for the overall trading pattern in a given

[18]In other words, under the null hypothesis, $\#$ of $\text{Buy}_{i,t}$ follows a binomial distribution with parameter $n = \#\text{ of Buy}_{i,t} + \#\text{ of Buy}_{i,t}$ and $p = \mathrm{E}[p_{i,t}]$.

quarter, therefore comparable across time.

Intuitively, herding is measured as the tendency of funds to trade a given bond together and in the same direction (either buy or sell) more often than would be expected if they trade independently. To differentiate between buy herding and sell herding, we also follow Wermers (1999) to define a buy herding measure (BHM) for bonds with a higher proportion of buyers than the market average and a sell herding measure (SHM) for bonds with a lower proportion of buyers than the market average. That is,

$$BHM_{i,t} = HM_{i,t} | p_{i,t} > \mathrm{E}[p_{i,t}], \tag{3.4}$$

and

$$SHM_{i,t} = HM_{i,t} | p_{i,t} < \mathrm{E}[p_{i,t}]. \tag{3.5}$$

By definition, for a given bond in a given quarter, it has either a BHM or an SHM (but not both), depending on its buying intensity relative to the market-wide buying intensity in that quarter.[19] Under the null hypothesis of no buy (sell) herding, BHM (SHM) of an individual bond in a given quarter is expected to be zero. If institutions sell in herds more frequently than they buy in herds, the average SHM should be significantly larger than the average BHM.

The LSV herding measure described above is by design estimated for a given group of institutions. In this paper, we first treat all investors as a single group and then treat each of the three types of investors, insurance companies, mutual funds, and pension funds, as an individual group. Note that, when calculating herding measures for each subgroup, we re-estimate the proxy for $\mathrm{E}[p_{i,t}]$ and the adjustment factor using trades within each subgroup only.

[19] Note that when calculating BHM (or SHM), the adjustment factor is recalculated conditional on $p_{i,t} > \mathrm{E}[p_{i,t}]$ (or $p_{i,t} < \mathrm{E}[p_{i,t}]$). For the occasional case when $p_{i,t} = \mathrm{E}[p_{i,t}]$, neither BHM nor SHM is calculated for that bond-quarter.

4 Empirical Results on Herding

In this section, we start with a descriptive analysis of institutional herding in corporate bond trading. We then use a panel regression approach to study the determinants of both sell herding and buy herding. Lastly, we provide evidence on the persistence in herding and examine the extent to which such persistence is driven by institutions' imitation behavior. In all analyses, we compare the results for different types of institutional investors, as we expect that their herding behavior may vary under different regulatory environments and payout policies.

4.1 Descriptive Analysis

Our descriptive analysis examines the level of institutional herding in trading corporate bonds and how it varies by investor type, activeness of trading, and credit rating. The results are summarized in Tables III and IV.

In Table III, Columns (1) and (2) show estimated levels of herding with all investors together, while the rest of the columns show herding estimates by investor type. The first block of rows show results from a baseline sample, where we require that the bond is traded by at least five institutions in a given quarter.[20] Results based on samples of more actively traded bonds are shown in the following rows.

The level of institutional herding in corporate bonds is high. As shown in the top row of Column (1), the mean herding measure for all institutions together is about 11 percent. Intuitively, this implies that if 100 institutions trade a given bond in a given quarter, approximately 11 more institutions trade on the same side of the market than would be expected if each institution trades bonds independently.

The results on the level of herding are robust to our choice of the minimum number of

[20] Such a requirement reflects a reasonable definition of a "herd." Note that when we apply this hurdle to each subgroup of investors, we require that bonds should be traded by at least five investors in that particular subgroup. Therefore the number of qualified bond-quarters in Column (2) is greater than the number of qualified bond-quarters in Columns (4), (6), and (8).

institutions trading on the bond. In fact, the level of herding increases substantially as more institutions trade on a bond, driven by herding on the sell side. This finding is different from what is documented for herding in stocks. For example, Wermers (1999) finds that the level of herding in stocks does not monotonically increase, but actually slightly decreases, as more mutual funds trade on the stock. This contrast is interesting, as it suggests that once a sell herd has formed in the corporate bond market, the addition of new traders tends to grow the herd.

The level of herding varies by investor type. Insurance companies, the largest investor group of corporate bonds, exhibit the greatest tendency to herd in bond trading, with an average herding measure of 13.2 percent. The herding measures for mutual funds and pension funds are lower but still fairly high, both at around 9 percent. Notably, for all investor types, our estimated level of institutional herding in corporate bonds is substantially higher than what is documented for stocks. For instance, Lakonishok, Shleifer, and Vishny (1992) find that the average level of herding in stocks by pension funds is 2.7 percent, much lower than our finding of 8.6 percent for bond pension funds (Column (5)). Wermers (1999) and Brown, Wei, and Wermers (2013) document that the average level of herding in stocks by equity mutual funds is 3.4 percent and 3.3 percent, respectively, also substantially lower than our finding of 9.6 percent for bond mutual funds (Column (3)).

We also find that sell herding is generally much stronger than buy herding, particularly so among mutual funds. Staying with the baseline case (the first block of rows), we can see that the overall sell herding measure is 12.3 percent, significantly stronger than the buy herding measure, which is about 9.8 percent. However, not all types of investors behave the same way. In fact, only mutual funds herd more strongly on the sell side, while pension funds and insurance companies herd more strongly on the buy side. This result with mutual funds is consistent with existing findings on herding in equities. For examples, Wermers (1999) and Brown, Wei, and Wermers (2013) find stronger sell-side herding in stocks by equity mutual funds.

Interestingly, the level of sell herding relative to buy herding increases as more institutions trade on a bond, as shown in rows of "BHM-SHM". Indeed, when we focus on bonds with at least 20 active institutional traders in a quarter, the level of sell herding significantly exceeds the level of buy herding for all types of bond investors, particularly so for mutual funds. This asymmetry between sell herding and buy herding among highly active bonds suggests that the corporate bond market is particularly susceptible to fire-sale risks.

Table III also provides a gauge on the "size of herd." The number of bond-quarters meeting the criteria of each sampling, shown in even-numbered columns, drops substantially as higher hurdles for trading activeness are applied. In particular, mutual funds and insurance companies start with almost the same amount of bond-quarters (around 140,000) when we require at least five active trades in a quarter. However, as we require at least 30 active trades, mutual funds still have about 14,000 bond-quarters, while insurers are left with fewer than 7,000 bond-quarters. This finding indicates that as a subgroup, mutual funds form larger herds much more frequently than other types of investors.

Table IV reports levels of herding for bonds in each rating group. We find that, consistent with our conjecture that herding would be more likely to occur among riskier bonds, the mean herding measure is 8.9, 11.6 and 21.8 percent for investment-grade, speculative-grade, and unrated bonds, respectively. We find similar patterns for all types of bond investors.

For the time trend of herding levels, Figure 3 shows that average buy herding levels trend down over time, mainly driven by mutual funds. Meanwhile, average sell herding levels trend up, almost entirely driven by mutual funds, suggesting increasing correlated sales among bond mutual funds.

4.2 Regression Analysis on the Determinants of Herding

Having documented a high level of institutional herding in corporate bonds, we now use a panel regression approach to explore the determining factors of such herding behavior. In these regressions, we do not explicitly test theories of herding. Rather, motivated by existing literature, we empirically test a wide range of factors that are potentially associated with herding, and draw inferences from our findings.

First, we include past performance of corporate bonds, represented by abnormal returns and rating changes. Empirical studies on equity herding suggests that institutional herding is related to their positive-feedback trading strategies. (see Grinblatt, Titman, and Wermers (1995) and Wermers (1999)). In particular, the level of buy herding is higher in stocks with higher previous-quarter returns, while the level of sell herding is higher in stocks with lower previous-quarter returns. We test if such momentum strategy exists for the corporate bond market,[21] and, if so, whether this herding-performance relationship is linear.

Second, we include variables for bond size and trading liquidity, as well as other bond characteristics, such as credit rating, age (i.e. time since issuance), and remaining time to maturity. Previous studies on equity herding find that the level of herding is higher in trades of certain subgroups of stocks. Specifically, Lakonishok, Shleifer, and Vishny (1992) document higher herding levels among small stocks, and Wermers (1999) finds higher herding levels among small, growth stocks, due in part to their low liquidity and noisy informational environment. Thus, we also explore whether herding is more prevalent in corporate bonds with certain characteristics that are related to trading liquidity.

Last but not least, we examine the persistence of herding behavior by including indicators on herding levels in past quarters. If herding in a particular bond persists after controlling for publicly observable bond characteristics, it implies either imitation behavior or autocorrelation of self-trading, which we will explore in depth in Section 4.3.

Specifically, we estimate the following model for buy and sell herding separately:

$$BHM_{i,t}(\text{or, } SHM_{i,t}) =$$
$$\alpha_{i,t} + \sum_{\tau=1}^{4} \beta_\tau RET_{i,t-\tau} + \sum_{\tau=1}^{2} \lambda_\tau RET^2_{i,t-\tau} + \sum_{\tau=0}^{1} \left(\gamma_\tau^U UpGd_{i,t-\tau} + \gamma_\tau^D DownGd_{i,t-\tau}\right)$$

[21] Jostova et al. (2013) document significant return momentum in noninvestment-grade bonds.

$$+\sum_{\tau=1}^{3}\left(\phi_{\tau}^{B}BHD_{i,t-\tau}+\phi_{\tau}^{S}SHD_{i,t-\tau}\right)+\delta LIQ_{i}+\sum_{k}\theta_{k}Character_{i,t}^{k}+FE\epsilon_{i,t} \quad (4.1)$$

The dependent variable is the buy (or sell) herding measure of bond i in quarter t. $RET_{i,t-\tau}$ is the abnormal return of bond i in quarter $t-\tau$. $RET^2_{i,t-\tau}$ is the squared abnormal return of bond i in quarter $t-\tau$. This term is intended to capture any nonlinearity in the sensitivity of herding behavior to past returns. $UpGd_{i,t-\tau}$ is a dummy variable that equals 1 if there is an upgrade for bond i during quarter $t-\tau$ and equals 0 otherwise. Similarly, $DownGd_{i,t-\tau}$ is a dummy variable that equals 1 if there is a downgrade for bond i during quarter $t-\tau$. $BHD_{i,t-\tau}$ and $SHD_{i,t-\tau}$ are dummy variables that indicate herding directions of bond i in quarter t. We also control for various bond characteristics such as bond liquidity, outstanding size, bond age, and number of years to maturity.[22] Finally, we use quarter and issuer fixed effects to control for unobservable heterogeneity over time and across issuers.

4.2.1 Determinants of Buy Herding

Table V presents the regression results for buy herding. In general, investors show a higher level of buy herding in corporate bonds with higher abnormal returns in the previous year, suggesting that bond investors follow positive-feedback strategies like equity investors do. As shown in Columns (1)–(4), the coefficients on bonds' abnormal returns in the previous four quarters are all positive and significantly different from zero. Regression results within each subgroup of investors show that mutual funds and pension funds react more to recent bond returns (previous two quarter returns for mutual funds and previous quarter return for pension funds), while insurance companies react with longer lags. We don't find evidence that top-performing bonds attract disproportionally larger herds. In fact, Columns (2)–(5) of Table V report a slightly concave relationship between the level of buy herding and past abnormal returns.

Coefficients on rating upgrade and downgrade dummies are small in magnitude and less

[22] For a full list of these dependent variables and the details about how they are calculated, see Appendix A.

significant in the full sample, but they show interesting dynamics among different types of investors. Specifically, insurance companies are more likely to herd to buy a bond if it has just experienced an upgrade, and less so after a downgrade, consistent with the fact that it is more costly for insurance companies to hold lower-rated bonds due to regulatory constraints. In contrast, mutual funds and pension funds are more likely to herd to buy after a rating downgrade, and less so after an upgrade, likely taking advantage of market frictions created by regulations that insurance companies are subject to.

Herding in previous quarters affects strongly current-quarter buy herding levels. Column (5) shows that buy herding tends to be lower if the bond experienced herding in recent quarters, regardless of whether it was from the buy side or from the sell side. These results suggest that buy herding is not persistent over quarters, while recent sell herding has a substantial and long-lasting negative influence on the current level of buy herding.

Other bond characteristics also help explain buy herding. First, investors are more likely to herd to buy speculative-grade bonds and bonds with smaller amounts outstanding, consistent with findings in the stock market by Lakonishok, Shleifer, and Vishny (1992) and Wermers (1999). Second, insurance companies form stronger herds to buy bonds that are newer and have longer time to maturity, while mutual funds and pension funds herd into seasoned bonds with longer time to maturity. Lastly, all investors show higher levels of buy herding in low-liquidity bonds, especially for pension funds.

4.2.2 Determinants of Sell Herding

In Table VI, we present the regression results for sell herding. Comparing R^2 results in Table VI with those in Table V, we find that the same set of independent variables have a lot more explanatory power for sell herding than for buy herding.

In general, investors show a higher level of sell herding in bonds with lower abnormal returns in the previous year. As shown in Columns (1)–(5) of Table VI, the coefficients on bonds' abnormal returns in the previous four quarters are all negative and significantly different from zero. Regression results within each subgroup of investors show that pension funds react more to recent bond returns, while both mutual funds and insurance companies react with longer lags. Compared to mutual funds, insurance companies form stronger sell herds in response to bad past performance.

More interestingly, we find evidence of a strong convex relationship between the level of sell herding and past abnormal returns of the bond, shown in Columns (2)–(5). Investors appear to herd disproportionally more to sell bonds with extremely bad performance. Such a robust convex relationship suggests that bad performance of a corporate bond could trigger a disproportionately large amount of simultaneous sales that would further depress its price—a downward spiral scenario. This finding clearly points to the potential vulnerabilities posed by sell-offs of corporate bond investors in market downturns, when they are increasingly likely to shed the same bonds as those bonds' performance deteriorates.

For all investors, sell herding intensifies as a bond's rating changes. In particular, the level of sell herding is significantly higher after rating downgrades, especially for mutual funds and insurance companies. The coefficient estimate in Column (5) implies that a downgrade of bond rating in the previous quarter corresponds to a 150 basis point increase in the level of sell herding. Interestingly, the level of sell herding is also significantly higher after rating upgrades. As shown in Column (5), an upgrade of bond rating in the previous quarter corresponds to a 130 basis point increase in the level of sell herding. These results imply that, for bonds that are sold with higher intensity than the market average, all recent updates in ratings (whether upgrades or downgrades) have contributed to the selling herds, reflecting the diversity and different objectives of institutional investors.

Past herding directions substantially affect current sell herding levels. As shown in Column (5) of Table VI, experiencing selling herds in previous three quarters corresponds to a combined 260 basis point increase in the current level of sell herding. These results show that recent sell herding substantially exacerbates current selling pressure of the bond, while recent buy herding does not alleviate it. This finding suggests that sell herding is strongly persistent. Such strong persistence in sell herding after controlling for publicly observable fund characteristics suggests that bond investors either imitate others or repeat their own trades when they sell, providing a clear evidence for intentional herding.

Other bond characteristics also contribute to explaining sell herding. First, investors, especially insurance companies, herd more to sell speculative-grade bonds than investment-grade bonds. Second, all investors show a higher level of sell herding in bonds with smaller amounts outstanding. Third, all investors form stronger herds to sell bonds that are older and have shorter time to maturity. Lastly, only insurance companies show a significantly lower level of sell herding in low-liquidity bonds, while the coefficient is insignificant for mutual funds and pension funds after controlling for other factors.

4.2.3 Robustness

Overall, we have found that corporate bond investors, like equity investors, follow positive-feedback strategies by herding to buy winning bonds and herding to sell losing bonds. This herding-to-performance relationship is nonlinear, in that extremely bad past performances lead to disproportionally large selling herds. In addition, different types of bond investors exhibit interesting dynamics in their reactions to rating-change events. When insurance companies respond to downgrades by reducing their buying herds due to regulations, mutual funds and pension funds take advantage of such market frictions to buy these downgraded bonds. We also document strong and long-lasting persistence in sell herding, which suggests that bond investors imitate others or repeat their own trades when they sell.

We conduct additional analyses to check the robustness of our results. First, we vary our ways of clustering standard errors. In reported results, standard errors are clustered at the individual bond level. We find that the significance of our results is not affected by either clustering standard errors at the quarter level or double-clustering at the bond-quarter level.

Second, to address the concern that some macro-factors may drive our results, we control for quarter fixed effects and report results in Column (4) of the two result tables. We further control for bond issuer fixed effects (identified by the first six digits of the bond CUSIP) to address the concern that institutional investors may have preference over some particular type of issuers and such preference may result in fundamental-driven herding. These results are reported in Column (5). Controlling for these fixed effects does not qualitatively change our main results.

Third, in reported regressions, we require that a bond should be actively traded by at least five investors in a given quarter to qualify for the calculation of either a buy herding measure or sell herding measure. Our main results remain robust and become even stronger if we require at least ten active trades. This robustness check eliminates the concern that our results are perhaps driven by some thinly traded bonds.

4.3 Persistence in Herding and Imitation Behavior

Our regression results have shown that, institutional herding in corporate bonds, especially sell herding, is persistent over time. In this subsection we provide further evidence on such persistence and look into its driving forces.

We first examine the transition probability of herding status over adjacent quarters. Specifically, in each quarter we sort bonds with at least five active trades into quintiles based on their buy (sell) herding measures. Bonds with various degrees of buy herding are sorted into quintiles "B1"–"B5," with "B5" representing the group of bonds with the highest buy herding levels. Bonds with various degrees of sell herding are sorted into quintiles "S1"–"S5," with "S5" representing the group of bonds with the highest sell herding measures. For bonds in each of the two sets of quintiles in a quarter, we track which quintile the bonds fall into next quarter.[23] Averaging over all quarters and bonds by their initial sorting, we obtain an empirical probability matrix over adjacent quarters, which we plot in Figure 4.

As we can see, in general, a bond is most likely to be sorted into the same buy/sell herding quintile as in the quarter before. Such a tendency is particularly strong for sell herding. For

[23] We require that bonds are traded by at least five investors in both quarters.

example, as shown in the top left panel, if a bond is in the highest sell herding quintile in the current quarter, the chance of its making the highest sell herding quintile in the next quarter is over 40 percent, and the chance of its making the second-highest sell herding quintile in the next quarter is almost 30 percent.

We now follow Sias (2004) to break down the herding persistence into imitation and habit components. Specifically, as pointed out by Sias (2004), the positive correlation of intertemporal herding can be driven either by institutional investors who follow others into and out of the same securities (i.e., imitation) or by individual institutional investors who follow their own last-quarter trades (i.e., habit). In particular, Sias (2004) shows that for equity institutional investors, "imitation" and "habit" contribute almost equally to the correlated intertemporal herding. To explore the underlying reasons for the intertemporal persistence in corporate bond trading, we estimate such decomposition in the following way. First, we estimate the level of persistence as the degree of autoregression of the buying fraction. We then use the formula of Sias (2004) to compute the imitation component and habit component.[24] The results are reported in Table VII.

First, we confirm that there is strong persistence in institutional trading in corporate bonds over adjacent quarters. As shown in Panel A, using the full sample of bond-quarters with at least one active institutional trader, the coefficient associated with the lagged standardized buying fraction averages 0.26, significantly different from zero at the 1% level. In other words, the correlation between institutional trading in bonds in this quarter and that in the previous quarter averages 0.26. This average correlation in bond trading is significantly higher than that in equity trading, which is about 0.12, as reported by Sias (2004). Moreover, this strongly positive intertemporal correlation in bond trading holds for all subgroups of institutional investors. In particular, insurance companies have a substantially higher intertemporal correlation in bond trading than mutual funds and pension funds. This finding echoes the earlier result that herding within the same quarter is also stronger among

[24]For full details of our estimation approach, see Appendix B.

insurance companies.

Second, our decomposition results show that, with all investors as a group, the intertemporal persistence in institutional trading is mostly driven by investors imitating others' past trades. Specifically, our point estimates show that, on average, only about one-fifth of the intertemporal correlation (i.e., 0.05 out of 0.26) is driven by institutional investors continuing to buy (or sell) the bonds they just bought (or sold) in the previous quarter, while much of the intertemporal correlation (i.e., 0.21 out of 0.26) is driven by investors imitating others' trades in the previous quarter. These results are in contrast to those in Sias (2004), who documents that the two factors contribute almost equally to the persistence in trading stocks.

Third, we find that while the imitation factor contributes dominantly to trading persistence for all types of investors, there are some variations across investors in their habit-driven trading. Specifically, both mutual funds and pension funds tend to reverse their own trades in the previous quarter, as opposed to the overall results discussed above. For these two types of investors, the following-self (or habit) terms are both negative, small in magnitude but statistically significant. In contrast, insurance companies load a higher portion on the following-self term, which makes up about one-third of the intertemporal correlation (i.e., 0.09 out of 0.26). When it comes to the following-others (or imitation) term, all types of investors have a strong tendency to follow their peers' trades in the previous quarter. In particular, for mutual funds and pension funds, the following-others term explains more than the entire persistence in their trading of corporate bonds, overshadowing the reversing effect cast by the negative following-self term.

To address the concern that our results on persistence may be driven by bonds with relatively few institutional traders, we further restrict the sample to bond-quarters with at least 5 and 10 institutional traders.[25] As shown in Panel B of Table VII, restricting the

[25]Such a concern is legitimate, demonstrated in the following example. Consider bond S (small) and bond L (large). Bond S is bought by one trader in the previous quarter and one trader in the current quarter, while bond L is bought by 80 percent of 100 traders in the previous quarter and 90 percent of 100 traders in the current quarter. Since we take into account only the fraction of buying rather than the base number

sample to bond-quarters with at least 5 traders actually generates even stronger persistence. Moreover, the portion of the correlation resulting from following others is substantially higher compared to the results in Panel A. More interestingly, the variations in the following-self trading patterns among different types of investors, as observed in Panel A, vanish as bonds are traded more actively. Further restricting the sample to bond-quarters with at least 10 traders yields qualitatively similar results, as shown in Panel C.

5 Price Impact of Herding

In this section, we explore the price impact and stability implications of institutional herding in the corporate bond market. Our findings of strong herding and its imitation motive raise the concern for financial stability: Does herding stabilize or destabilize bond prices? By definition, herding stabilizes prices if herding-induced price changes are permanent, while herding destabilizes prices if herding-induced price changes reverse course subsequently. Answers to this question will help us evaluate the implications of herding for market efficiency and financial stability. In addition, studying price impact helps us draw inference about the motives underlying the observed herding. As pointed out by Bikhchandani and Sharma (2000), fundamental-driven herding is generally efficient and facilitates price discovery, while imitation-driven herding is generally inefficient and can lead to price reversals and excess volatility.

5.1 Methodology: A Portfolio Approach

We use the standard portfolio approach to analyze whether institutional herding generates price impacts in the corporate bond market, and if so, whether on the buy or sell side. To make inference about the extent of price reversal, we examine the relation between herding

of traders, bond S will contribute more to the intertemporal correlation than bond L because bond S has a higher correlation of fractions of buying over the adjacent quarters. However, it is clear that the trading pattern of bond L represents the concept of "herding" and is more robust, as the trading pattern of bond S is more likely to be random.

levels and bond returns in current and following quarters. We also investigate the relation between herding and past returns to further determine the extent to which herding is related to positive-feedback trading strategies. Because we find much stronger persistence in sell herding than in buy herding, we also explore possible asymmetry in their price impact.

To this end, we design our analysis as follows. First, as in Section 4.3, in each quarter we sort bonds into two sets of quintile portfolios: "B1"−"B5" and "S1"−"S5," where portfolios B1 and B5 include bonds with the lowest and highest buy herding levels, respectively, and portfolios S1 and S5 include bonds with the lowest and highest sell herding levels, respectively. Based on this sorting, we form three zero-investment portfolios: "S5-B5", "S5-S1", and "B1-B5", where portfolio S5-B5 represents a zero-investment portfolio that longs bonds that are sold by the largest herds (S5) and shorts bonds that are bought by the largest herds (B5). Portfolios S5-S1 and B1-B5 are defined in a similar way. It is important to note that all three portfolios represent contrarian trading strategies that go against the market trends.

We examine the quarterly equal-weighted abnormal returns for each of these contrarian portfolios before, during, and after the portfolio formation quarter. Following Bessembinder, Maxwell, and Venkataraman (2006), we estimate abnormal returns by computing the difference between a bond's raw return (which takes into account both bond price changes and accrued interests) and the average return on a set of bonds with similar credit rating, industry, and remaining term to maturity.[26] If institutional herding is associated with positive-feedback strategies, we would expect to see negative abnormal returns for all three portfolios (S5-B5, S5-S1, and B1-B5) before the portfolio formation quarter. More important, we look at the long-term price impact of institutional herding after the portfolio formation quarter. Specifically, a significant return reversal after portfolio formation would indicate that herding drives bond prices away from their fundamental values and destabilizes bond prices, while a flat return after portfolio formation would imply that herding helps price discovery and thus stabilizes bond prices.

[26]See Appendix A for details on how we calculate the abnormal bond returns.

5.2 Results

We present our price impact results in three parts: the baseline results based on the overall herding sample with all institutional investors as a group; the results by bond type and investor type; and the results for the sub-period of the recent financial crisis.

5.2.1 Baseline Results

Panel A of Table VIII presents the quarterly abnormal returns around the herding quarters for the three zero-investment portfolios described earlier. It shows that a higher level of sell herding (S5 compared to S1) is associated with lower abnormal returns prior to and during the portfolio formation quarter, and that a higher level of buy herding (B5 compared to B1) is associated with higher past abnormal returns. In addition, bonds heavily sold (S5) on average underperform bonds heavily bought (B5) by about 67 to 111 basis points in terms of quarterly abnormal return in the four quarters prior to portfolio formation and 44 basis points during the portfolio formation quarter. These results suggest that positive-feedback trading strategies contribute to both buy and sell herding.

In terms of post-herding price dynamics, bond returns revert immediately after the portfolio formation quarter for portfolios S5-B5 and S5-S1. In particular, the abnormal returns on both the S5-B5 and S5-S1 portfolios turn from negative to positive in the quarter immediately following portfolio formation and remain positive for additional five quarters. For buy herding, however, the abnormal returns on portfolio B1-B5 continue to be negative in the quarter immediately following portfolio formation and largely diminish afterward. These results suggest that institutional sell herding destabilizes corporate bond prices and buying herding helps price discovery and stabilizes prices.

5.2.2 Results by Bond Type and Investor Type

In Panel B of Table VIII, we present the price impact results for three subgroups of corporate bonds, speculative-grade (junk) bonds, small bonds, and illiquid bonds.[27] We find that both positive-feedback trading strategies before the portfolio formation quarter and return reversals after the portfolio formation quarter are much stronger for these subgroups of bonds, especially junk bonds. Specifically, in terms of quarterly abnormal return, junk bonds heavily sold (S5) on average underperform bonds heavily bought (B5) by about 153 to 271 basis points during the four quarters prior to portfolio formation, but they outperform by about 63 to 214 basis points after portfolio formation. For small bonds and illiquid bonds, the patterns of positive-feedback trading and return reversals are similar to those for junk bonds and larger in magnitude than those estimated for all bonds together. Results of portfolio returns on S5-S1 and B1-B5 for these three subgroups of bonds (not reported but illustrated in Figure 5) also show that return reversals are mainly driven by sell herding.

We graphically illustrate these results in Figure 5. Panel A plots quarterly abnormal returns on portfolios S5-B5, S5-S1, and B1-B5 constructed with the full sample as well as subgroups of bonds, and Panel B shows cumulative abnormal returns (where the value at portfolio formation quarter t is indexed to zero). For the full sample, the S5-B5 portfolio lost 4 percent in the four quarters leading up to portfolio formation quarter t but earns an abnormal return of 2.5 percent within six quarters afterward. For junk bonds, the return reversal is much stronger, with a cumulative abnormal return of 6 percent in six quarters after portfolio formation. Compared to junk bonds, small bonds and illiquid bonds display similar but smaller-in-magnitude patterns. Panel B also presents the stark contrast between the cumulative abnormal returns on portfolio S5-S1 and those on portfolio B1-B5 after portfolio formation. It shows that sell herding exerts large yet transitory pressure on bond prices, driving the bond prices substantially away from their fundamental values and causing

[27] A bond is defined as "small" if its size, measured by its amount outstanding, is in the bottom two quintiles in a given quarter, and a bond is defined as "illiquid" if its lifetime liquidity measure is in the bottom two quintiles. The construction of the liquidity measure is described in details in Appendix A.

excessive price volatility. In contrast, buy herding is likely to speed up price discovery. This finding is consistent with our hypothesis that in the corporate bond market, the underlying motives of sell herding and buy herding are asymmetric (i.e. imitation vs. fundamental), so are their implications for financial stability.

We also look into the price impact of herding by different types of investors. Figure 6 plots cumulative abnormal returns on portfolios S5-B5, S5-S1, and B1-B5 for insurance companies, mutual funds, and pension funds. The return reversal patterns are very similar across different institution types, suggesting that herding by all three types of institutions contributes to the price dynamics of bonds.[28]

5.2.3 Price Impacts at Times of Stress

As our sample period covers the global financial crisis of 2007–2009, it is natural to compare the bond price dynamics during the crisis period with those during the non-crisis period. The results are shown in Figure 7, where we plot cumulative abnormal returns on portfolios formed during the crisis and normal times, with the crisis period defined as 2007:Q3–2009:Q2 and the normal period defined as 1998:Q4–2006:Q1 and 2010:Q3–2014:Q3.[29]

Not surprisingly, the price reversal patterns in portfolio S5-B5 and S5-S1 are much stronger during the crisis period than during the non-crisis period. During the crisis, sell herding exerts drastic temporary price pressure, causing prices of heavily sold bonds to plunge more than 10 percent in a few quarters leading up to quarter t. As price pressure dissipates, prices of these bonds revert about 8 percent within two quarters after portfolio formation. In contrast, during normal times, the cumulative abnormal return after portfolio formation is less than 2 percent. Therefore, a trading strategy based on our portfolio method is most profitable when the market is under stress, when liquidity provision through acting

[28] The exact price impact of each type of institution is hard to disentangle because of correlated herding in certain bonds between subgroups of investors. We conduct additional tests (not reported) and find that mutual funds and pension funds are more likely to herd together than with insurance companies, and that sell herding across different types of investors is more positively correlated than buy herding.

[29] We exclude 2006:Q2–2007:Q2 and 2009:Q3–2010:Q2 from the non-crisis period to avoid picking up price dynamics from the crisis period.

as a contrarian is riskiest.

5.2.4 Remarks

Our finding that institutional herding—in particular institutions' sell herding—destabilizes bond prices is new to the fixed-income literature. This evidence differs from the results in earlier papers on the stock market, in which the authors didn't find any significant price impact by herding (Lakonishok, Shleifer, and Vishny (1992); Nofsinger and Sias (1999); and Wermers (1999)). Our evidence is consistent with papers on the stock market that focus on more recent periods (Brown, Wei, and Wermers (2013); Dasgupta, Prat, and Verardo (2011)) but is much stronger in magnitude.[30] Our evidence clearly points to the vulnerabilities associated with correlated trades by institutional investors. In particular, the price-destabilizing effect is strongest for the riskiest bonds and during periods of market distress, when liquidity is most needed. This finding highlights the role of herding in amplifying financial stability risks during market downturns.

6 Conclusions

Institutional investors have been playing an increasingly important role in the fixed-income markets, such as the market for corporate bonds, boosted by the significant growth of these investors' market shares in recent years. Therefore, if they tend to cluster in trading these relatively illiquid securities, the resulting price impact of sell herding may cause fast fund outflows and asset fire sales, especially during market downturns. These dynamics could become an amplification channel of financial systemic risks.

In this paper, we find that institutional investors do trade in herds in the U.S. corporate

[30]Temporary price impact and return reversals may exist for various reasons. Downward-sloping demand curves (Da and Gao (2009); Ambrose, Cai, and Helwege (2012)), dealers' inventory cost considerations (Jegadeesh and Titman (1995), Khang and King (2004)), or limits to arbitrage caused by market frictions (e.g., Li, Zhang, and Kim (2011)) may all lead to such a finding. We document the strong relationship between sell herding and return reversal, but not exclude the effects of these other factors. In fact, they may all work together to reinforce each other.

bond market. Indeed, the average level of herding in this market, particularly among lower-rated bonds, is much higher than what previous studies have documented for equity markets. We also find institutional herding in the corporate bond market is highly persistent over time, especially in selling, driven mostly by institutions following their peers' trades.

We find that among major types of investors in corporate bonds, mutual funds trade bonds most actively and have shown a growing tendency to herd when they sell but not when they buy. Mutual funds' secular increase in their level of sell herding is particularly concerning for financial stability because these funds offer significant liquidity transformation, in that they allow for daily redemption while investing in relatively illiquid assets (Chernenko and Sunderam (2016)). When mutual funds sell in herds to meet investor redemption, their demand for immediate liquidity may trigger large price concessions.[31] Moreover, we find that when funds herd to sell, the sensitivity of sell herding to past performance displays a convex relationship, suggesting that they react more strongly and unanimously to extremely bad past performance—a recipe for a run type of scenario.

Most important, we document an asymmetry in the price impact of institutional herding, which highlights the role of sell herding in amplifying financial stability risks during market downturns. While buy herding is associated with permanent price impact that is consistent with price discovery, sell herding results in transitory yet significant price distortions and thus excess price volatility. This price-destabilizing effect of sell herding is especially strong for high-yield bonds, small bonds, and illiquid bonds, and during the global financial crisis period.

Overall, our analysis suggests that further research is warranted to address the current concerns about financial stability risks associated with herding behavior of corporate bond investors. We have shown that the underlying causes of herding behavior in this market are mixed, in that the impact of sell herding on bond prices is consistent with theories of imitation herding, which predict loss of information efficiency and excess volatility. In contrast, the

[31]Mutual funds may suspend redemption when facing heavy liquidation needs, which may trigger even larger and wider-spread concerns.

effect of buy herding on bond prices is consistent with theories of fundamental-driven herding, which aids price discovery. Given the strong price impact of sell herding, especially during crises, it is critical to understand more about the exact nature of the observed trading behavior. Moreover, future research is needed to deepen our understanding of the differential roles in herding played by fund managers, funds' shareholders, and securities dealers.

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Appendix

A Independent Variables Used in Model (4.1)

- Lagged abnormal return. We calculate quarterly raw bond returns using Merrill Lynch pricing data, adjusting for interest and coupon payments. In particular, the raw return for bond i in quarter t is calculated as

$$r_{i,t} = \frac{(P_{i,t+1} + I_{i,t+1}) - (P_{i,t} + I_{i,t}) + D_{i,t} \times C_{i,t} \times (1 + r_{Libor,t})^{\Delta t}}{P_{i,t} + I_{i,t}}, \tag{A.1}$$

  where $P_{i,t}$ is bond i's price at the start of quarter t, $I_{i,t}$ is accrued interest and $D_{i,t}$ is an indicator of whether coupon payment $C_{i,t}$ occurs during quarter t. The abnormal bond return is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, financial/nonfinancial classification, and time to maturity in that quarter.

- Bond rating change. We use rating information obtained from three rating agencies (Moody's, Standard & Poor's, and Fitch) to compute an average rating after converting letter ratings into numerical ratings.[32] Change of rating is calculated as the difference between the average numerical rating at the current quarter-end and that at the previous quarter-end. We also differentiate between upgrades and downgrades in regression specifications.

- Lagged levels of herding. It is possible that institutional herding in bonds is not only within one quarter but persists across multiple quarters as well. To control for this potential persistence, we generate dummies for different levels of herding in past quarters: BHD (i.e. Bought by Herd Dummy) and SHD (i.e., Sold by Herd Dummy). If bond i is sold with higher intensity than the average market trend and traded by at least five funds in quarter $t-\tau$, it will be assigned with $BHD_{i,t-\tau} = 0$ and $SHD_{i,t-\tau} = 1$. Similarly, if bond i is bought with higher intensity than the average market trend and traded by at least five funds in quarter $t-\tau$, it will be assigned with $BHD_{i,t-\tau} = 1$ and $SHD_{i,t-\tau} = 0$. If bond i is bought/sold with exactly the same intensity as the market trend OR traded by fewer than five funds in quarter $t-\tau$, it will be assigned with $BHD_{i,t-\tau} = 0$ and $SHD_{i,t-\tau} = 0$.

- Bond liquidity. To examine the correlation between herding and bond liquidity, we use TRACE intraday transaction data to estimate three bond liquidity measures that are commonly used in the literature.

[32] Our general rule of conversion is to assign bigger numbers to higher ratings. For instance, all AAA-rated bonds across the three agencies are assigned number 23, and all D-rated bonds are assigned number 1.

– Amihud (2002) price impact measure, defined as

$$Liq_{i,d}^{Amihud} = \frac{1}{N_{i,d}} \sum_{j=1}^{N_{i,d}} \frac{|P_{i,d}^{j} - P_{i,d}^{j-1}|/P_{i,d}^{j-1}}{Q_{i,d}^{j}}, \tag{A.2}$$

where $P_{i,d}^{j}$ and $Q_{i,d}^{j}$ are, respectively, the price and the size of the j-th trade (ordered by trading time) of bond i at day d, and $N_{i,d}$ is the total number of trades of bond i at day d. The Amihud measure indicates illiquidity in that a larger value implies that a trade of a given size would move the price more, suggesting higher illiquidity or lower market depth. See Kyle (1985).

– Effective bid-ask spread based on the Roll (1984) model, which is a proxy for bond liquidity costs and defined as:[33]

$$Liq_{i,d}^{Roll} = 2\sqrt{-cov(\Delta P_{i,d}^{j}, \Delta P_{i,d}^{j-1})}. \tag{A.3}$$

– Indirect measure of bid-ask spread using the interquartile range (IQR) of trade prices, defined as the difference between the 75th percentile and 25th percentile of prices for the day:[34]

$$Liq_{i,d}^{IQR} = \frac{P_{i,d}^{75th} - P_{i,d}^{25th}}{P_{i,d}^{50th}} \times 100. \tag{A.4}$$

We then incorporate all three measures to calculate a comprehensive liquidity measure for each bond in each quarter.[35] To address the concern of possible endogeneity between a bond's liquidity and its herding level in a given quarter, we take a lifetime average of the bond's liquidity measures and use it as the bond's overall liquidity measure.

- Other bond characteristics, including a dummy variable indicating whether the bond is investment-grade or not, size of outstanding (in thousands of dollars), age (measured as the number of quarters since issuance), and time to maturity (measured in quarters).

[33] See also Bao, Pan, and Wang (2011) for an application of this measure in examining the illiquidity of corporate bonds and its asset-pricing implications.

[34] The IQR is similar to the commonly used price range, but, compared with the latter, it is less subject to the influence of extreme values. As a liquidity proxy, the IQR is in the same spirit as both the realized bid-ask spread proposed by Chakravarty and Sarkar (1999) and the volatility measures proposed by Alexander, Edwards, and Ferri (2000) and Hong and Warga (2000).

[35] In each quarter, we sort bonds into deciles based on the three liquidity measures and define the average decile number as a comprehensive liquidity measure for a bond in that quarter. For example, if a bond is sorted into "9," "8," and "10" deciles based on the three liquidity measures, respectively, it then has a comprehensive liquidity measure of "9" (the average of 9, 8, and 10) in that quarter.

B Decomposing Intertemporal Correlation in Trading

Following Sias (2004), we define the standardized fraction of institutional investors buying bond i in quarter t (denoted as $q_{i,t}$) as

$$q_{i,t} = \frac{p_{i,t} - \overline{p}_t}{\sigma(p_{i,t})}, \tag{B.1}$$

where $p_{i,t}$ is the fraction of trading institutions buying bond i in quarter t, $\overline{p_t}$ is the cross-sectional average (across I securities) of $p_{i,t}$, and $\sigma(p_{i,t})$ is the cross-sectional standard deviation (across I securities) of $p_{i,t}$. By definition, standardized fraction $q_{i,t}$ has zero mean and unit variance. In each quarter, we estimate a cross-sectional regression of the standardized buying fraction $q_{i,t}$ on its lag term $q_{i,t-1}$:

$$q_{i,t} = \beta_t q_{i,t-1} + \epsilon_{i,t}. \tag{B.2}$$

Because both the dependent and independent variables are standardized and scaled to zero mean, the intercept term of the regression model is zero, and the coefficient β_t is simply the correlation between institutional demand in this quarter and in the previous quarter. To examine whether such intertemporal correlations are driven by imitating others or following ones own habits, following Sias (2004), we decompose β_t into two components as follows:

$$\begin{aligned}
\beta_t =& \rho(q_{i,t}, q_{i,t-1}) \\
=& \frac{1}{(I_t - 1)\sigma(p_{i,t})\sigma(p_{i,t-1})} \sum_{i=1}^{I_t} \left[\sum_{n=1}^{N_{i,t}} \frac{(D_{n,i,t} - \overline{p}_t)(D_{n,i,t-1} - \overline{p}_{t-1})}{N_{i,t} N_{i,t-1}} \right] \\
&+ \frac{1}{(I_t - 1)\sigma(p_{i,t})\sigma(p_{i,t-1})} \sum_{i=1}^{I_t} \left[\sum_{n=1}^{N_{i,t}} \sum_{m=1, m \neq n}^{N_{i,t-1}} \frac{(D_{n,i,t} - \overline{p}_t)(D_{m,i,t-1} - \overline{p}_{t-1})}{N_{i,t} N_{i,t-1}} \right],
\end{aligned} \tag{B.3}$$

where I_t is the number of bonds traded by institutional investors in quarter t, $N_{i,t}$ is the number of institutional investors trading bond i in quarter t, and $D_{n,i,t}$ is a dummy variable that equals 1 (0) if the trader n is a buyer (seller) of bond i in quarter t. The first term is the portion of the correlation that results from institutional investors following themselves into and out of the same bond. In particular, it will be positive if institutions tend to follow their previous quarter's trades, and it will be negative if institutions tend to reverse their previous quarter's trades. The second term is the portion of the correlation that results from institutional investors following others.

We also re-estimate the regression model within each subgroup of investors (mutual fund, pension fund, and insurance company) and recalculate the decomposition for each subgroup. Specifically, for a given institution type W, the estimation and decomposition of the coefficient are done as follows:

$$\begin{aligned}
\beta_t^W =& \rho(q_{i,t}^W, q_{i,t-1}^W) \\
=& \frac{1}{(I_t^W - 1)\sigma(p_{i,t}^W)\sigma(p_{i,t-1}^W)} \sum_{i=1}^{I_t^W} \left[\sum_{n=1}^{N_{i,t}^W} \frac{(D_{n,i,t} - \overline{p}_t^W)(D_{n,i,t-1} - \overline{p}_{t-1}^W)}{N_{i,t}^W N_{i,t-1}^W} \right] \\
&+ \frac{1}{(I_t^W - 1)\sigma(p_{i,t}^W)\sigma(p_{i,t-1}^W)} \sum_{i=1}^{I_t^W} \left[\sum_{n=1}^{N_{i,t}^W} \sum_{m=1, m \neq n}^{N_{i,t-1}^W} \frac{(D_{n,i,t} - \overline{p}_t^W)(D_{m,i,t-1} - \overline{p}_{t-1}^W)}{N_{i,t}^W N_{i,t-1}^W} \right],
\end{aligned} \tag{B.4}$$

where I_t^W is the number of bonds traded by type-W investors in quarter t, $N_{i,t}^W$ is the number of type-W investors trading bond i in quarter t, and $p_{i,t}^W$ is the raw fraction of trading institutions buying bond i in quarter t, calculated within type-W.

Figure 1: **Thomson Reuters Lipper eMAXX Coverage on Institutional Holdings of Corporate Bonds**

This figure plots time series of eMAXX data coverage on institutional holdings of corporate bonds between 1998:Q3 and 2014:Q3, broken down into three institutional investor types: insurance companies, mutual funds, and pension funds. All other institutional investors, whose holdings make up about 1 percent of total observations, are excluded. Figure 1a plots the time series of the number of institutional investors by type, excluding foreign funds. Figure 1b plots the time series of the number of corporate bonds held by institutional investors, limited to U.S.-dollar-denominated bonds issued by U.S. companies with fixed coupons. Figure 1c plots the time series of the dollar value of corporate bond holdings (in billions) covered by eMAXX.

Figure 1a: Number of Institutional Investors

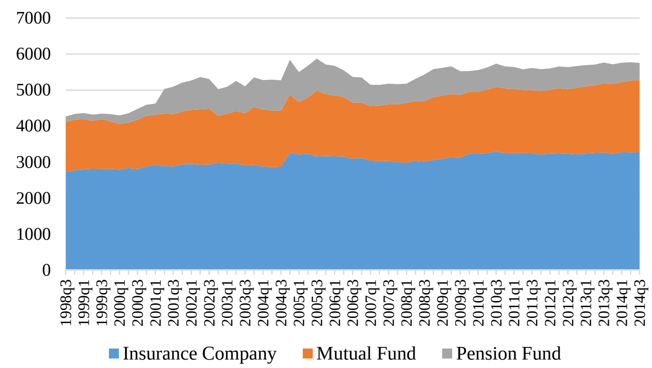


Figure 1b: Number of Coporate Bonds

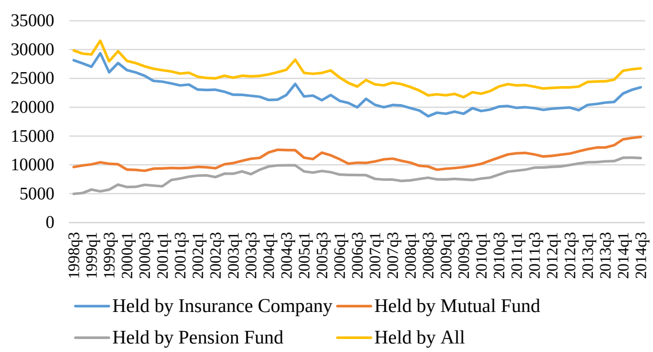


Figure 1c: Holding Amount of Corporate Bonds in Billion $

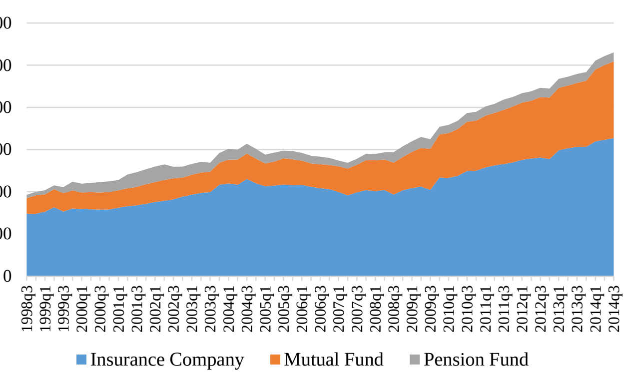
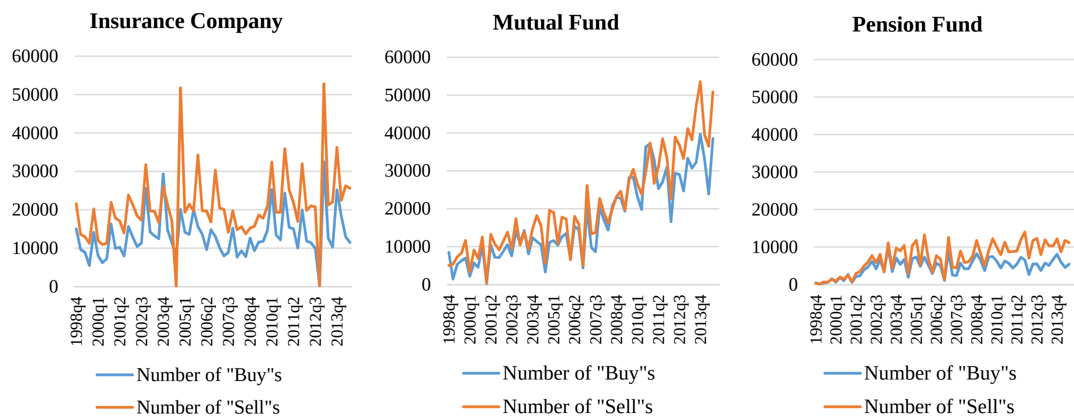


Figure 2: **Total Trading Frequencies and Volumes of Corporate Bonds**

This figure plots time series of total trading frequencies and volumes of corporate bonds between 1998:Q3 and 2014:Q3, broken down into three institutional investor types: insurance companies, mutual funds, and pension funds. Bonds that are issued or maturing within one year are excluded from this chart. We define a "sell" ("buy") of bond i by fund j in quarter t if fund j's holdings of bond i increase (decrease) from the end of quarter $t-1$ to the end of quarter t. Panel A plots time series of total trading (buying and selling) frequencies by investor type. Panel B plots time series of total trading (buying and selling) volumes by investor type.

Panel A: Total Trading Frequency, by Investor Type



Panel B: Total Trading Volume, in Billion $, by Investor Type

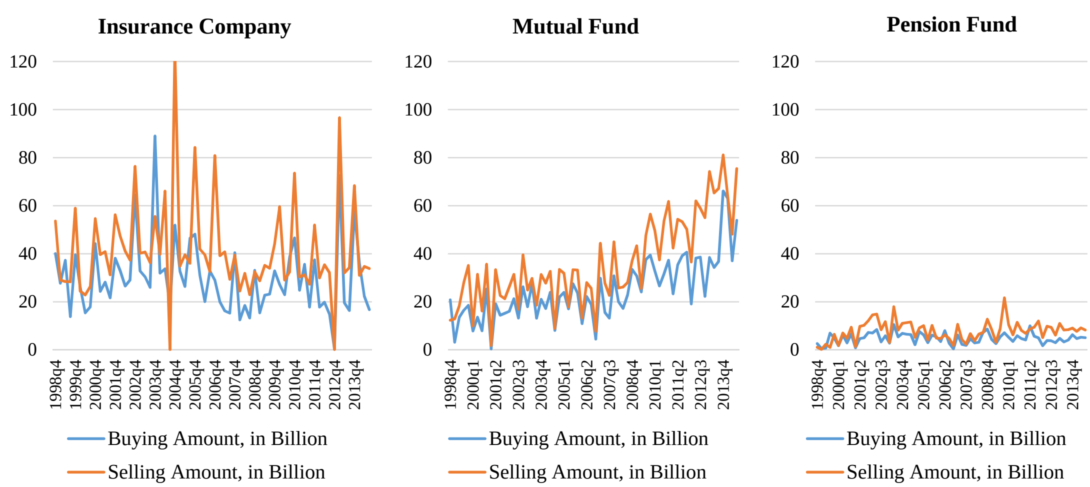
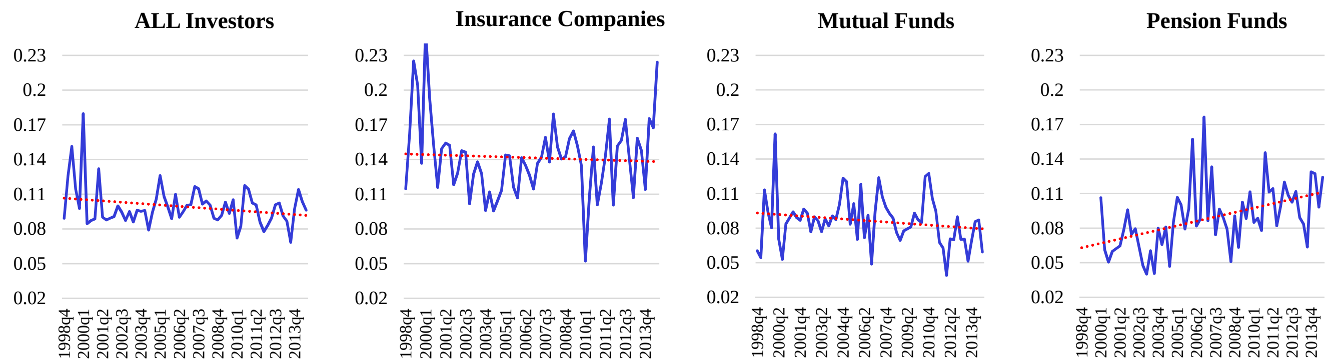


Figure 3: **Time Series of Mean Buy (Sell) Herding Levels**

This figure plots time series of mean buy herding measures (Panel A) and mean sell herding measures (Panel B) of corporate bond investors between 1998:Q3 and 2014:Q3, also broken down into subgroups. Bonds that are issued or maturing within one year are excluded. The herding measure $HM_{i,t}$ for a given bond-quarter is defined as $HM_{i,t} = |p_{i,t} - \mathrm{E}[p_{i,t}]| - \mathrm{E}|p_{i,t} - \mathrm{E}[p_{i,t}]|$, where $p_{i,t}$ is the proportion of funds trading bond i during quarter t that are buyers. $\mathrm{E}|p_{i,t} - \mathrm{E}[p_{i,t}]|$ is calculated under the null hypothesis that funds trade bonds independently and randomly. The buy herding measure $BHM_{i,t}$ is calculated for bonds with a higher proportion of buyers than the average and is defined as $BHM_{i,t} = HM_{i,t}|p_{i,t} > \mathrm{E}[p_{i,t}]$. Similarly, the sell herding measure $SHM_{i,t}$ is calculated for bonds with a higher proportion of sellers than the average and is defined as $SHM_{i,t} = HM_{i,t}|p_{i,t} < \mathrm{E}[p_{i,t}]$. Herding measures for each subgroup of investors are all recalculated within each subgroup. In each quarter, we average buy (sell) herding measures over bonds with a higher (lower) proportion of buyers than the market average and traded by at least five funds.

Panel A: Buy Herding Measure, by Investor Type



Panel B: Sell Herding Measure, by Investor Type

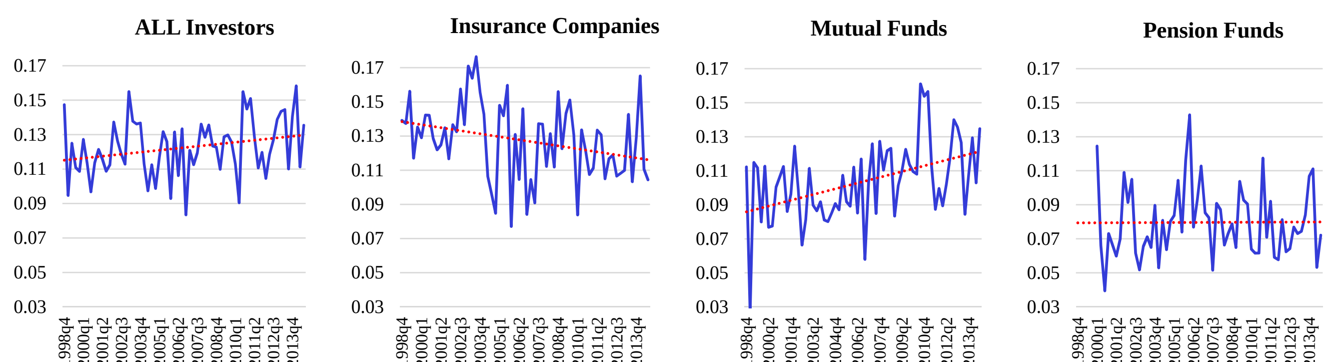


Figure 4: **Persistence of Herding over Adjacent Quarters**

This figure plots histograms of future herding levels of bonds based on their current herding levels. Over the 1998:Q3–2014:Q3 sample period, in each quarter we sort bonds with at least five active trades into quintiles based on their buy (sell) herding measures. Bonds bought with higher intensity than the market average are sorted into quintile “B1”-“B5” (indicated by “1” to “5” in the chart), with “B5” (or “5” in the chart) representing the group of bonds with the highest buy herding measures. Bonds sold with higher intensity than the market average are sorted into quintile “S5”-“S1” (indicated by “-5” to “-1” in the chart), with “S5” (or “-5” in the chart) representing the group of bonds with the highest sell herding measures. The figure shows the probability of being sorted into a certain buy (or sell) quintile in the following quarter conditional on what buy (or sell) quintile the bond currently belongs in, given that the bonds are traded by at least five institutional investors in both quarters. Bonds issued or maturing within one year are excluded.

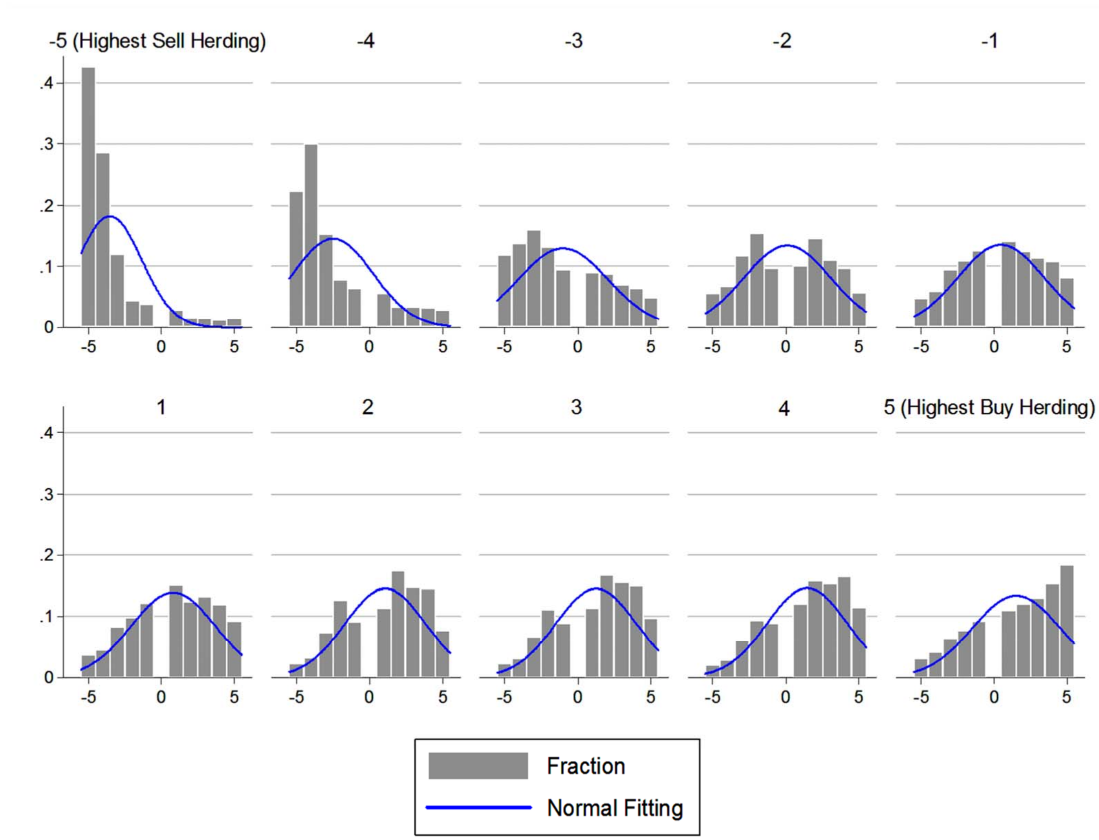
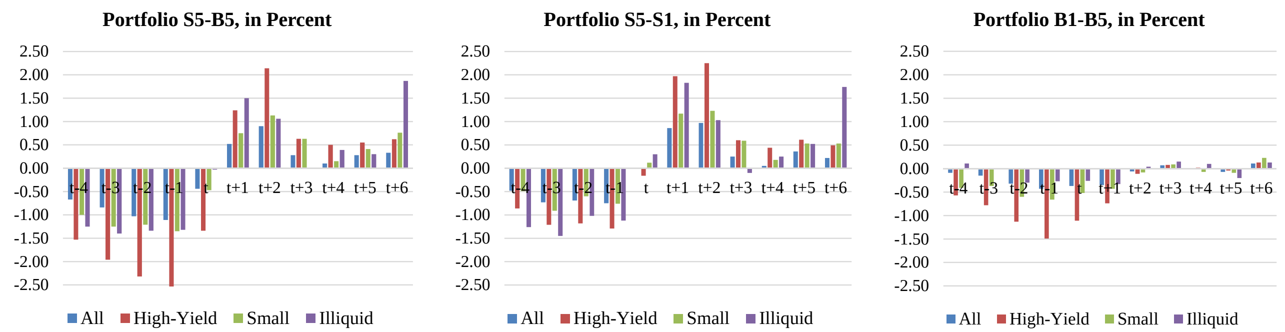


Figure 5: **Abnormal Returns on Zero-Investment Portfolios, by Bond Type**

This figure illustrates abnormal returns (both quarterly and cumulative) on zero-investment portfolios S5-B5, S5-S1, and B1-B5 before and after portfolio formation. Bonds' abnormal return is computed as the raw quarterly return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, financial/nonfinancial classification, and time to maturity. The cumulative abnormal return is indexed to zero in the portfolio formation quarter. In each quarter, bonds bought with higher intensity than the market average are sorted into quintile "B1" to "B5," with "B5" representing the group of bonds with the highest buy herding measures. Bonds sold with higher intensity than the market average are sorted into quintile "S5" to "S1", with "S5" representing the group of bonds with the highest sell herding measures. Zero-investment portfolio S5-B5 is constructed in a contrarian manner, long the equal-weighted portfolio containing bonds that institutional investors most strongly sold as a herd (i.e., S5) and short the equal-weighted portfolio containing bond that institutional investors most strongly bought as a herd (i.e., B5). Portfolios S5-S1 and B1-B5 are similarly defined. This figure also exhibits abnormal returns on portfolios constructed from bond subgroups. A "small" bond is a bond whose outstanding amount is in the bottom two size quintiles in a quarter. An "illiquid" bond is a bond whose overall liquidity measure is in the bottom two liquidity quintiles.

Panel A: Quarterly Abnormal Returns, in Percent



Panel B: Cumulative Abnormal Returns

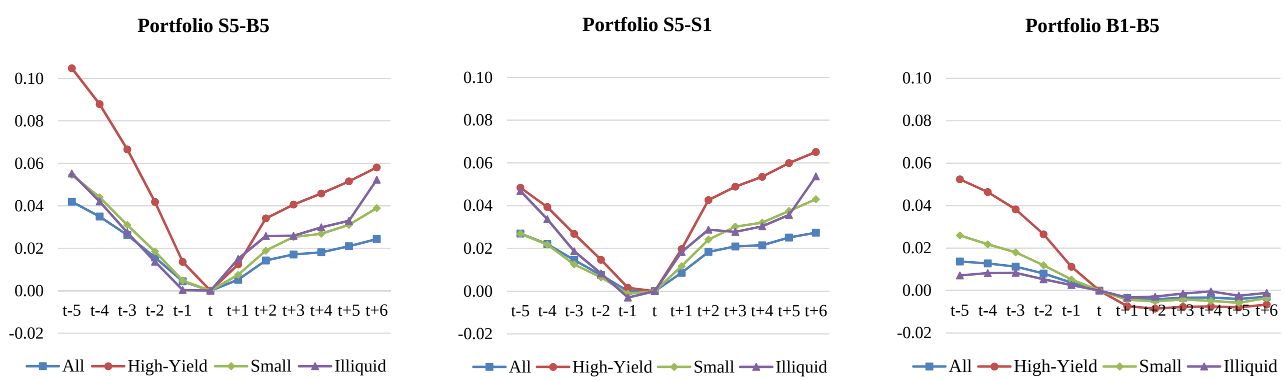


Figure 6: **Cumulative Abnormal Returns on Zero-Investment Portfolios, by Investor Type**

This figure illustrates cumulative abnormal returns on zero-investment portfolios S5-B5, S5-S1, and B1-B5 constructed based on herding measures of investor subgroups, before and after portfolio formation quarter t. Bonds' quarterly abnormal return is computed as the raw quarterly return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, financial/nonfinancial classification, and time to maturity. The cumulative abnormal return is indexed to zero in the portfolio formation quarter. Within each subgroup of investors (insurance company, mutual fund, or pension fund), in each quarter, bonds bought with higher intensity than the submarket average are sorted into quintile "B1" to "B5," with "B5" representing the group of bonds with the highest subgroup buy herding measures. Bonds sold with higher intensity than the submarket average are sorted into quintile "S5" to "S1," with "S5" representing the group of bonds with the highest subgroup sell herding measures. For each subgroup of investors, zero-investment portfolio S5-B5 is constructed in a contrarian manner, long the equal-weighted portfolio containing bonds that the subgroup of investors most strongly sold as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that the subgroup of investors most strongly bought as a herd (i.e., B5). Portfolios S5-S1 and B1-B5 are similarly defined. For each subgroup of investors, bonds traded by fewer than five investors of that subgroup in a given quarter are excluded.

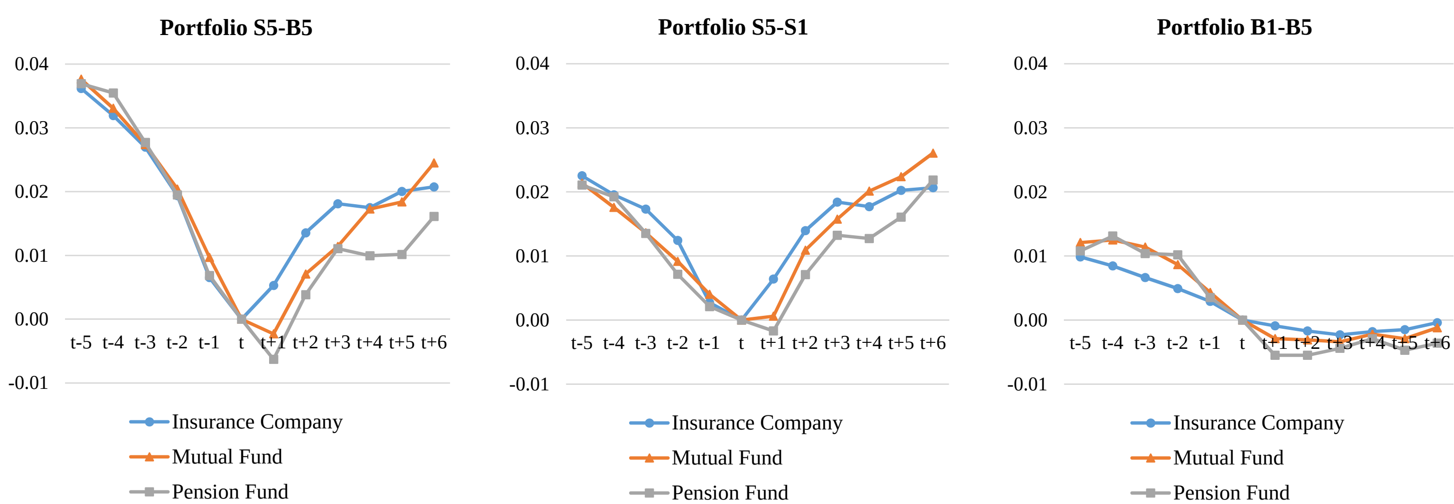


Figure 7: **Cumulative Abnormal Returns on Zero-Investment Portfolios during the 2007–2009 Crisis**

This figure illustrates cumulative abnormal returns on zero-investment portfolios S5-B5, S5-S1, and B1-B5 constructed based on herding measures during the global financial crisis and normal times. Bonds' quarterly abnormal return is computed as the raw quarterly return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, financial/nonfinancial classification, and time to maturity. The cumulative abnormal return is indexed to zero in the portfolio formation quarter. In each quarter, bonds bought with higher intensity than the market average are sorted into quintile "B1" to "B5," with "B5" representing the group of bonds with the highest buy herding measures. Bonds sold with higher intensity than the market average are sorted into quintile "S5" to "S1," with "S5" representing the group of bonds with the highest sell herding measures. Zero-investment portfolio S5-B5 is constructed in a contrarian manner, long the equal-weighted portfolio containing bonds that investors most strongly sold as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that investors most strongly bought as a herd (i.e., B5). Portfolios S5-S1 and B1-B5 are constructed in a similar way. Bonds traded by fewer than five investors in a given quarter are excluded. Crisis period is defined as 2007:Q3–2009:Q2, and noncrisis period is defined as 1998:Q3–2005:Q4 and 2010:Q4–2014:Q3. Note that we track portfolio returns four quarters before and six quarters after the portfolio formation quarter, and our definition of crisis/noncrisis period controls for the spillover effect.

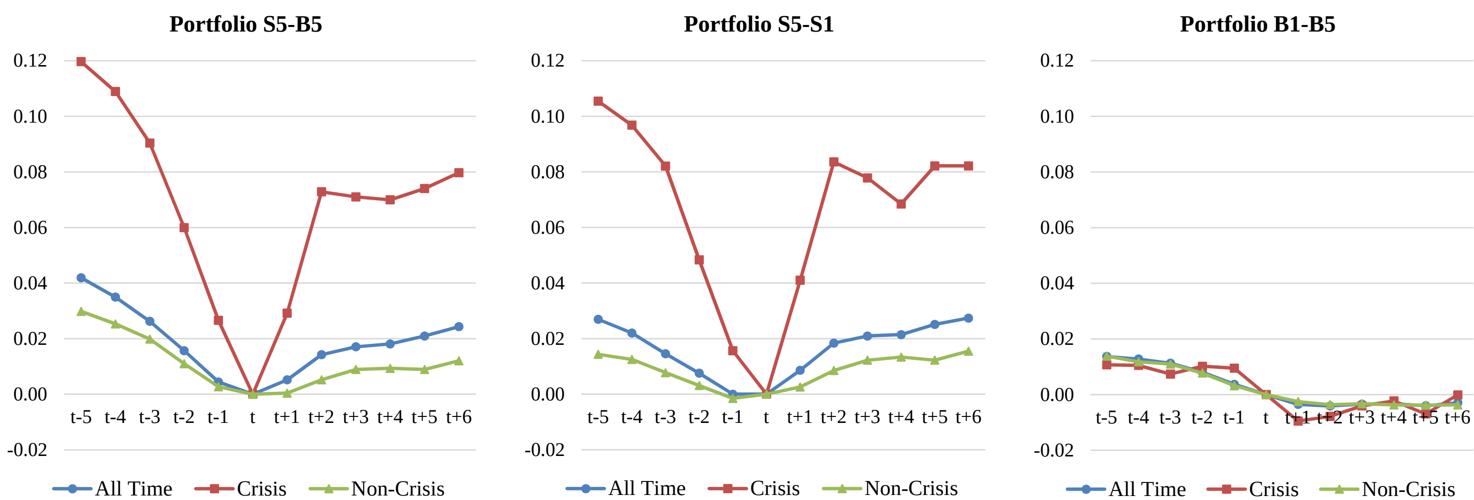


Table I: **Summary Statistics of the Average Investor in Thomson Reuters Lipper eMAXX**

This table provides summary statistics for corporate bond holdings of an average eMAXX institutional investor, broken down into three time intervals (1998:Q3–2006:Q4, 2007:Q1–2010:Q4, and 2011:Q1–2014:Q3) and three types (insurance company, mutual fund, and pension fund). In the "Holding" columns, we average total dollar values and numbers of corporate bonds across all funds and all quarters in each subperiod. In the "Quarterly Trading" columns, we define a fund as a buyer (seller) of bond i in quarter t if its holdings of bond i increase (decrease) from the end of quarter $t-1$ to the end of quarter t. (Note that when a fund first purchases a certain bond, it has no holding of that bond in the previous quarter, and when a fund liquidates its position in a certain bond, it sometimes does not have a "zero" holding of that bond in the next quarter. We take these special cases into consideration and include all "initial buying" and "liquidating selling" in our calculation.) Therefore, for each fund in each quarter, we can count the number of bonds sold and bought by that fund. We then average the number of trading across all funds and all quarters in each subperiod. In the "Quarterly Active Trading" columns, we exclude "buying" and "selling" of bonds that are issued or maturing within one year from the calculation.

		Holding		Quarterly Trading		Quarterly Active Trading (Excl. New and Maturing Bonds)	
Type of Investors	Period	Holding Amount (in Million $)	Number of Bonds Held	Number of Selling	Number of Buying	Number of Selling	Number of Buying
All	1998-2006	264	75	11	11	8	5
	2007-2010	294	93	14	16	10	8
	2011-2014	403	134	20	21	13	9
Insurance Company	1998-2006	322	83	11	9	7	5
	2007-2010	346	89	10	9	6	4
	2011-2014	451	121	12	12	8	5
Mutual Fund	1998-2006	174	58	12	13	9	6
	2007-2010	266	95	21	26	15	14
	2011-2014	409	151	31	36	21	17
Pension Fund	1998-2006	236	72	12	13	9	6
	2007-2010	152	111	21	23	15	10
	2011-2014	191	168	29	29	20	10

Table II: **Summary Statistics of an Average Bond in Thomson Reuters Lipper eMAXX**

This table provides summary statistics for an average corporate bond held by eMAXX investors, broken down into three time intervals (1998:Q3–2006:Q4, 2007:Q1–2010:Q4, and 2011:Q1–2014:Q3) and two risk levels (investment-grade and high-yield). Bonds that are issued or maturing within one year are excluded from this table. In the "Bond Characteristics" columns, we average amount outstanding (in million \$), bond age, and time-to-maturity across all bonds and all quarters in each subperiod. In the "Holding Information" columns, for each bond in each quarter, we count the number of eMAXX investors that have nonzero holdings of the bond and aggregate holdings across all of these investors. Then we take averages across all bonds and all quarters in each subperiod. In the "Quarterly Trades" columns, we define a fund as a buyer (seller) of bond i in quarter t if its holdings of bond i increase (decrease) from the end of quarter $t-1$ to the end of quarter t. (Note that when a fund first purchases a certain bond, it has no holding of that bond in the previous quarter, and when a fund liquidates its position in a certain bond, it sometimes does not have a "zero" holding of that bond in the next quarter. We take these special cases into consideration and include all "initial buying" and "liquidating selling" in our calculation.) Therefore, for each bond in each quarter, we can count the number of institutions that sell and buy that bond. We then average the number of sellers and buyers across all bonds and all quarters in each subperiod.

		Bond Characteristics			Holding Information		Quarterly Trades	
Type of Bonds	Period	Outstanding Amount (in Million \$)	Years from Issuance	Years to Maturity	Number of Investors	Amount Held by eMaxx Investors (in Million \$)	Number of Investors Who Sell	Number of Investors Who Buy
All	1998-2006	397	4	9	15	167	9	7
	2007-2010	631	5	8	24	215	12	9
	2011-2014	662	4	9	34	246	13	9
Investment-Grade	1998-2006	464	4	10	20	227	8	7
	2007-2010	756	5	10	35	276	11	10
	2011-2014	736	5	10	54	301	12	9
High-Yield	1998-2006	308	4	7	21	118	11	8
	2007-2010	444	4	7	27	158	16	11
	2011-2014	545	4	6	31	181	16	10

Table III: **Mean Herding Measures (in percent) of Corporate Bond Investors, by Investor Type**
Based on Thomson Reuters Lipper eMAXX

This table reports mean herding measures of corporate bond institutional investors over the sample period 1998:Q3–2014:Q3, excluding bonds that are issued or maturing within a year. The herding measure $HM_{i,t}$ for a given bond-quarter is defined as $HM_{i,t} = |p_{i,t} - \mathrm{E}[p_{i,t}]| - \mathrm{E}|p_{i,t} - \mathrm{E}[p_{i,t}]|$, where $p_{i,t}$ is the proportion of funds trading bond i during quarter t that are buyers. The proxy used for $\mathrm{E}[p_{i,t}]$ is the proportion of all bond trades by institutional investors during quarter t that are buys. $\mathrm{E}|p_{i,t} - \mathrm{E}[p_{i,t}]|$ is calculated under the null hypothesis that funds trade bonds independently and randomly. The buy herding measure $BHM_{i,t}$ is calculated for bonds with a higher proportion of buyers than the average and is defined as $BHM_{i,t} = HM_{i,t}|p_{i,t} > \mathrm{E}[p_{i,t}]$. Similarly, the sell herding measure $SHM_{i,t}$ is calculated for bonds with a higher proportion of sellers than the average and is defined as $SHM_{i,t} = HM_{i,t}|p_{i,t} < \mathrm{E}[p_{i,t}]$. Column (1) of this table presents the mean of $HM_{i,t}$, $BHM_{i,t}$, and $SHM_{i,t}$, averaged across all bond-quarters traded by the number of funds indicated by the row heading, and Column (2) reports the number of bond-quarters that are included in the calculation. This table also reports mean herding measures for each subgroup of investors, with $HM_{i,t}$, $BHM_{i,t}$, and $SHM_{i,t}$ all recalculated within each subgroup. For example, Column (3)×Row (6) shows the mean of $BHM_{i,t}$ (calculated for the subgroup of mutual funds only), which is averaged over all bond-quarters with higher buying intensity than the market and traded by at least 10 mutual funds, and Column (4)×Row (6) shows that there are 43,328 bond-quarters qualified for the calculation of this mean. We also compute the difference between the mean of $BHM_{i,t}$ and $SHM_{i,t}$ and report the significance of it being different from zero. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Number of Active Trades	Herding Measures		All eMAXX Investors (1)	(2)	Mutual Funds (3)	(4)	Pension Funds (5)	(6)	Insurance Companies (7)	(8)
≥ 5	HM	(1)	11.08***	(250,784)	9.62***	(139,045)	8.63***	(49,981)	13.18***	(139,160)
	BHM	(2)	9.75***	(134,763)	8.38***	(75,874)	9.04***	(24,378)	13.32***	(72,984)
	SHM	(3)	12.30***	(116,021)	10.82***	(63,171)	7.88***	(25,600)	12.53***	(66,175)
	BHM-SHM	(4)	−2.55***		−2.43***		1.16***		0.79***	
≥ 10	HM	(5)	11.37***	(155,892)	9.94***	(76,817)	9.37***	(16,989)	15.19***	(58,454)
	BHM	(6)	9.85***	(87,947)	8.49***	(43,328)	9.39***	(8,321)	14.27***	(30,100)
	SHM	(7)	13.15***	(67,945)	11.65***	(33,489)	9.21***	(8,668)	15.94***	(28,354)
	BHM-SHM	(8)	−3.29***		−3.16***		0.18		−1.67***	
≥ 20	HM	(9)	11.64***	(78,700)	10.79***	(29,757)	10.26***	(3,199)	18.10***	(16,791)
	BHM	(10)	9.75***	(45,023)	8.46***	(16,425)	9.45***	(1,600)	15.88***	(7,914)
	SHM	(11)	14.08***	(33,677)	13.60***	(13,332)	11.02***	(1,599)	20.03***	(8,877)
	BHM-SHM	(12)	−4.34***		−5.14***		−1.57***		−4.13***	
≥ 30	HM	(13)	12.01***	(44,601)	12.00***	(14,046)	11.52***	(839)	20.96***	(6,601)
	BHM	(14)	9.73***	(25,383)	8.73***	(7,492)	9.50***	(421)	18.59***	(2,796)
	SHM	(15)	14.96***	(19,218)	15.68***	(6,554)	13.50***	(418)	22.66***	(3,805)
	BHM-SHM	(16)	−5.22***		−6.95***		−4.00***		−4.06***	

Table IV: **Mean Herding Measures (in percent) of Corporate Bond Investors, by Investor Type and Bond Rating** Based on Thomson Reuters Lipper eMAXX

This table reports mean herding measures of corporate bond institutional investors over the sample period 1998:Q3–2014:Q3, excluding bonds that are issued or maturing within a year and broken into investment-grade and high-yield (junk) bonds. The herding measure $HM_{i,t}$ for a given bond-quarter is defined as $HM_{i,t} = |p_{i,t} - \mathrm{E}[p_{i,t}]| - \mathrm{E}|p_{i,t} - \mathrm{E}[p_{i,t}]|$, where $p_{i,t}$ is the proportion of funds trading bond i during quarter t that are buyers. The proxy used for $\mathrm{E}[p_{i,t}]$ is the proportion of all bond trades by institutional investors during quarter t that are buys. $\mathrm{E}|p_{i,t} - \mathrm{E}[p_{i,t}]|$ is calculated under the null hypothesis that funds trade bonds independently and randomly. The buy herding measure $BHM_{i,t}$ is calculated for bonds with a higher proportion of buyers than the average and is defined as $BHM_{i,t} = HM_{i,t}|p_{i,t} > \mathrm{E}[p_{i,t}]$. Similarly, the sell herding measure $SHM_{i,t}$ is calculated for bonds with a higher proportion of sellers than the average and is defined as $SHM_{i,t} = HM_{i,t}|p_{i,t} < \mathrm{E}[p_{i,t}]$. Columns (1)-(3) report the mean of $HM_{i,t}$, $BHM_{i,t}$, and $SHM_{i,t}$, averaged across all bond-quarters with ratings indicated by the column heading and the number of trades indicated by the row heading. This table also reports mean herding measures for each subgroup of investors, with $HM_{i,t}$, $BHM_{i,t}$, and $SHM_{i,t}$ all recalculated within each subgroup. We also compute the difference between the mean of $BHM_{i,t}$ and $SHM_{i,t}$ and report the significance of it being different from zero. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

		All eMAXX Investors			Mutual Funds		Pension Funds		Insurance Companies	
# of Active Trades	Herding Measure	Investment Grade (1)	High Yield (2)	Not Rated (3)	Investment Grade (4)	High Yield (5)	Investment Grade (6)	High Yield (7)	Investment Grade (8)	High Yield (9)
≥ 5	HM	8.85***	11.61***	21.82***	7.90***	10.66***	7.63***	8.99***	10.93***	14.61***
	BHM	8.68***	10.16***	21.93***	7.52***	8.88***	8.62***	9.02***	11.85***	15.65***
	SHM	8.71***	12.74***	21.52***	8.16***	12.04***	6.25***	8.59***	8.86***	13.40***
	BHM-SHM	−0.03	−2.58***	0.41*	−0.64***	−3.16***	2.37***	0.43***	2.98***	2.25***
≥ 10	HM	9.68***	11.84***	24.83***	8.36***	10.85***	8.36***	9.65***	13.10***	16.77***
	BHM	8.99***	10.35***	25.00***	7.78***	8.86***	9.30***	9.26***	12.87***	16.72***
	SHM	10.66***	13.22***	24.67***	9.19***	12.67***	7.21***	9.90***	13.13***	16.67***
	BHM-SHM	−1.68***	−2.87***	0.34	−1.42***	−3.81***	2.09***	−0.64***	−0.26**	0.05
≥ 20	HM	10.54***	12.02***	27.17***	9.34***	11.43***	8.86***	10.51***	16.50***	20.17***
	BHM	9.08***	10.15***	27.81***	7.83***	8.66***	9.61***	9.17***	14.58***	18.76***
	SHM	12.93***	13.94***	26.89***	11.75***	14.18***	7.92***	11.75***	18.56***	20.91***
	BHM-SHM	−3.85***	−3.79***	0.91	−3.92***	−5.52***	1.69**	−2.58***	−3.98***	−2.15***
≥ 30	HM	11.07***	12.37***	28.65***	10.67***	12.49***	9.42***	12.21***	19.67***	22.95***
	BHM	9.19***	10.06***	29.92***	8.26***	8.73***	9.76***	9.29***	17.43***	21.69***
	SHM	14.15***	14.77***	28.21***	14.31***	16.02***	8.72***	14.51***	21.65***	23.41***
	BHM-SHM	−4.96***	−4.71***	1.71	−6.06***	−7.29***	1.04	−5.22***	−4.22***	−1.73*

Table V: **Determinants of Buy Herding Levels (by Investor Type)**

This table reports regression results of determinants of buy herding measures. The dependent variable is the buy herding measure of bond i in quarter t. $\text{Ab\_Ret}_{t-\tau}$ is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar ratings, classification, and time to maturity in quarter $t-\tau$. $\text{Upgrade}_{t-\tau}$ ($\text{Downgrade}_{t-\tau}$) is a dummy that equals 1 if there is an upgrade (downgrade) of ratings in quarter $t-\tau$ and equals 0 otherwise. $\text{BHD}_{t-\tau}$ (i.e., Bought in Herd Dummy) and $\text{SHD}_{t-\tau}$ (i.e., Sold in Herd Dummy) indicate herding directions and levels in quarter $t-\tau$. In particular, BHD = 0 and SHD = 1 if the bond is sold with higher intensity than the market average and traded by at least five funds, BHD = 1 and SHD = 0 if the bond is bought with higher intensity than the market average and traded by at least five funds, and BHD = 0 and SHD = 0 if the bond is bought or sold with exactly the same intensity as the market average or traded by less than five funds. Low_Liq equals 1 if the bond is in the bottom two quintiles of the overall liquidity measure. Age_t and (Time-to-)Maturity_t are measured in quarters. Standard errors are clustered at the bond (CUSIP) level with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent Variables: Buy Herding Measure								
	All					Mutual	Pension	Insurance
	(1)	(2)	(3)	(4)	(5)	Fund	Fund	Company
Ab_Ret_{t-1}	0.040∗∗∗	0.046∗∗∗	0.045∗∗∗	0.050∗∗∗	0.045∗∗∗	0.028∗∗∗	0.061∗∗∗	0.011
	(4.97)	(5.70)	(5.52)	(6.17)	(5.27)	(2.77)	(3.41)	(0.52)
Ab_Ret_{t-2}	0.030∗∗∗	0.033∗∗∗	0.031∗∗∗	0.042∗∗∗	0.037∗∗∗	0.027∗∗∗	−0.003	0.047∗∗
	(4.29)	(4.21)	(3.99)	(5.27)	(4.46)	(2.68)	(−0.15)	(2.26)
Ab_Ret_{t-3}	0.023∗∗∗	0.022∗∗∗	0.020∗∗∗	0.023∗∗∗	0.017∗∗	0.010	0.022	0.032∗∗
	(3.13)	(3.10)	(2.83)	(3.21)	(2.24)	(1.17)	(1.37)	(2.02)
Ab_Ret_{t-4}	0.013∗	0.014∗	0.012∗	0.014∗	0.009	−0.004	−0.030∗	0.030∗
	(1.81)	(1.84)	(1.65)	(1.84)	(1.07)	(−0.44)	(−1.90)	(1.67)
Ab_Ret^2_{t-1}		−0.006	−0.005	−0.005	−0.006∗∗	−0.004	−0.013∗∗∗	0.004
		(−1.35)	(−1.16)	(−1.37)	(−1.99)	(−1.39)	(−3.00)	(0.61)
Ab_Ret^2_{t-2}		−0.004	−0.003	−0.006∗∗	−0.007∗∗	−0.003	0.003	−0.077
		(−1.07)	(−0.93)	(−2.15)	(−2.43)	(−1.02)	(0.23)	(−1.15)
Upgrade_t	0.000	0.000	0.000	0.001	0.001	−0.002	−0.007	0.001
	(0.07)	(0.06)	(0.24)	(0.68)	(0.68)	(−1.13)	(−0.17)	(0.34)
Upgrade_{t-1}	0.003∗	0.003∗	0.003∗	0.002	0.002	0.001	0.001	0.012∗∗∗
	(1.72)	(1.70)	(1.83)	(1.40)	(1.29)	(0.41)	(0.11)	(3.75)
Downgrade_t	−0.004∗∗∗	−0.004∗∗∗	−0.004∗∗∗	−0.003∗	−0.004∗∗	−0.001	0.006	−0.012∗∗∗
	(−2.81)	(−2.79)	(−2.95)	(−1.77)	(−2.54)	(−0.42)	(1.40)	(−4.06)
Downgrade_{t-1}	0.001	0.002	0.001	0.001	−0.001	0.007∗∗∗	0.009∗∗	−0.013∗∗∗
	(0.92)	(0.97)	(0.76)	(0.51)	(−0.46)	(3.05)	(1.99)	(−4.34)
BHD_{t-1}			0.004∗∗	0.001	−0.001	−0.012∗∗∗	−0.005	−0.001
			(2.19)	(0.31)	(−0.46)	(−5.57)	(−1.54)	(−0.68)
BHD_{t-2}			−0.007∗∗∗	−0.007∗∗∗	−0.007∗∗∗	−0.018∗∗∗	−0.016∗∗∗	−0.008∗∗∗
			(−4.05)	(−4.10)	(−3.68)	(−8.82)	(−4.53)	(−4.04)
BHD_{t-3}			−0.011∗∗∗	−0.012∗∗∗	−0.011∗∗∗	−0.026∗∗∗	−0.028∗∗∗	−0.011∗∗∗
			(−7.20)	(−7.07)	(−6.31)	(−13.00)	(−7.77)	(−5.25)
SHD_{t-1}			−0.013∗∗∗	−0.016∗∗∗	−0.016∗∗∗	−0.031∗∗∗	−0.034∗∗∗	−0.017∗∗∗
			(−7.57)	(−9.30)	(−8.51)	(−13.66)	(−8.73)	(−6.95)
SHD_{t-2}			−0.013∗∗∗	−0.013∗∗∗	−0.011∗∗∗	−0.019∗∗∗	−0.019∗∗∗	−0.018∗∗∗
			(−7.08)	(−7.26)	(−6.00)	(−8.37)	(−4.90)	(−7.13)
SHD_{t-3}			−0.013∗∗∗	−0.015∗∗∗	−0.013∗∗∗	−0.027∗∗∗	−0.030∗∗∗	−0.014∗∗∗
			(−7.43)	(−8.11)	(−6.75)	(−12.22)	(−7.37)	(−5.43)
Inv_Grade_t	−0.004∗∗∗	−0.004∗∗∗	−0.008∗∗∗	−0.008∗∗∗	−0.009∗∗∗	−0.005	−0.002	−0.007
	(−3.72)	(−3.75)	(−6.94)	(−7.04)	(−3.34)	(−1.44)	(−0.38)	(−1.45)
$\log(\text{Size}_t)$	−0.008∗∗∗	−0.008∗∗∗	−0.005∗∗∗	−0.006∗∗∗	−0.004∗∗∗	0.001	−0.010∗∗	−0.008∗∗∗
	(−12.73)	(−12.71)	(−7.27)	(−7.59)	(−3.10)	(0.61)	(−2.46)	(−3.76)
$\log(\text{Age}_t)$	0.000	0.000	−0.001	−0.002∗∗	−0.001	0.005∗∗∗	0.003	−0.018∗∗∗
	(0.32)	(0.33)	(−1.45)	(−2.40)	(−1.05)	(3.88)	(0.96)	(−11.13)
$\log(\text{Maturity}_t)$	0.009∗∗∗	0.009∗∗∗	0.008∗∗∗	0.009∗∗∗	0.009∗∗∗	0.002∗∗∗	0.012∗∗∗	0.021∗∗∗
	(15.10)	(15.10)	(13.91)	(13.95)	(14.28)	(2.82)	(4.97)	(17.60)
Low_Liq	0.008∗∗∗	0.008∗∗∗	0.008∗∗∗	0.007∗∗∗	0.005∗∗∗	0.003∗	0.014∗∗∗	0.004∗
	(7.07)	(7.07)	(7.20)	(6.90)	(4.06)	(1.66)	(3.66)	(1.73)
Quarter FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.009	0.009	0.014	0.027	0.049	0.096	0.082	0.096
N of Obs	92,695	92,695	92,695	92,695	92,695	56,915	18,400	50,136

Table VI: **Determinants of Sell Herding Levels (by Investor Type)**

This table reports regression results of determinants of sell herding measures. The dependent variable is the sell herding measure of bond i in quarter t. Ab_Ret$_{t-\tau}$ is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar ratings, classification, and time to maturity in quarter $t-\tau$. Upgrade$_{t-\tau}$ (Downgrade$_{t-\tau}$) is a dummy that equals 1 if there is an upgrade (downgrade) of ratings in quarter $t-\tau$ and equals 0 otherwise. BHD$_{t-\tau}$ (i.e., Bought in Herd Dummy) and SHD$_{t-\tau}$ (i.e., Sold in Herd Dummy) indicate herding directions and levels in quarter $t-\tau$. In particular, BHD = 0 and SHD = 1 if the bond is sold with higher intensity than the market average and traded by at least five funds, BHD = 1 and SHD = 0 if the bond is bought with higher intensity than the market average and traded by at least five funds, and BHD = 0 and SHD = 0 if the bond is bought or sold with exactly the same intensity as the market average or traded by less than five funds. Low_Liq equals 1 if the bond is in the bottom two quintiles of the overall liquidity measure. Age$_t$ and (Time-to-)Maturity$_t$ are measured in quarters. Standard errors are clustered at the bond (CUSIP) level with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent Variables: Sell Herding Measure								
	All					Mutual	Pension	Insurance
	(1)	(2)	(3)	(4)	(5)	Fund	Fund	Company
Ab_Ret$_{t-1}$	−0.060***	−0.084***	−0.079***	−0.074***	−0.066***	−0.031***	−0.033**	−0.057***
	(−6.96)	(−10.08)	(−9.54)	(−9.09)	(−7.75)	(−2.72)	(−2.05)	(−4.84)
Ab_Ret$_{t-2}$	−0.050***	−0.064***	−0.054***	−0.053***	−0.041***	−0.045***	−0.062***	−0.048***
	(−4.98)	(−6.92)	(−5.95)	(−5.86)	(−4.41)	(−3.59)	(−3.41)	(−3.47)
Ab_Ret$_{t-3}$	−0.048***	−0.042***	−0.034***	−0.034***	−0.039***	−0.029**	−0.022	−0.033***
	(−4.98)	(−4.49)	(−3.70)	(−3.71)	(−4.13)	(−2.46)	(−1.58)	(−2.60)
Ab_Ret$_{t-4}$	−0.037***	−0.033***	−0.024**	−0.024***	−0.022**	−0.034***	−0.011	−0.065***
	(−3.78)	(−3.42)	(−2.53)	(−2.61)	(−2.20)	(−2.90)	(−0.71)	(−4.31)
Ab_Ret$^2_{t-1}$		0.078***	0.072***	0.066***	0.054***	0.038*	0.028	0.016***
		(4.15)	(4.12)	(3.90)	(3.05)	(1.93)	(1.00)	(4.18)
Ab_Ret$^2_{t-2}$		0.075***	0.065***	0.064***	0.037***	−0.011	0.070***	0.005
		(5.35)	(5.04)	(4.93)	(3.13)	(−0.80)	(4.81)	(1.40)
Upgrade$_t$	0.002	0.002	0.001	0.004*	0.004*	0.005**	0.011***	0.003
	(1.06)	(0.94)	(0.64)	(1.77)	(1.77)	(2.02)	(3.09)	(0.87)
Upgrade$_{t-1}$	0.013***	0.013***	0.013***	0.013***	0.013***	0.010***	0.005	0.011***
	(6.27)	(6.29)	(6.20)	(6.22)	(5.89)	(3.61)	(1.25)	(3.45)
Downgrade$_t$	0.007***	0.006***	0.006***	0.008***	0.006***	0.005*	0.007**	0.006**
	(3.74)	(3.28)	(3.24)	(4.67)	(3.02)	(1.84)	(1.97)	(2.36)
Downgrade$_{t-1}$	0.020***	0.018***	0.017***	0.018***	0.015***	0.015***	0.004	0.016***
	(10.79)	(10.00)	(9.39)	(9.81)	(7.56)	(5.52)	(1.19)	(6.75)
BHD$_{t-1}$			−0.004*	−0.009***	−0.003*	−0.005	−0.006**	−0.004*
			(−1.90)	(−4.57)	(−1.65)	(−1.35)	(−2.06)	(−1.94)
BHD$_{t-2}$			0.000	0.000	0.001	0.000	−0.005*	0.005**
			(0.31)	(0.02)	(0.62)	(0.15)	(−1.83)	(2.43)
BHD$_{t-3}$			−0.002	−0.005**	0.001	0.001	0.003	0.003
			(−1.15)	(−2.32)	(0.54)	(0.55)	(1.12)	(1.23)
SHD$_{t-1}$			0.022***	0.017***	0.014***	0.010***	0.012***	0.008***
			(9.86)	(7.37)	(6.77)	(3.84)	(4.16)	(3.68)
SHD$_{t-2}$			0.017***	0.016***	0.008***	0.004	0.005	0.015***
			(6.89)	(6.33)	(3.89)	(1.57)	(1.58)	(6.21)
SHD$_{t-3}$			0.009***	0.005**	0.004**	0.005*	0.012***	0.008***
			(3.81)	(2.22)	(2.11)	(1.74)	(4.02)	(3.32)
Inv_Grade$_t$	−0.038***	−0.037***	−0.029***	−0.026***	−0.015***	−0.005	0.016***	−0.036***
	(−23.42)	(−22.53)	(−17.31)	(−15.38)	(−5.49)	(−1.35)	(3.08)	(−9.62)
log(Size$_t$)	−0.018***	−0.018***	−0.019***	−0.021***	−0.031***	−0.038***	−0.032***	−0.031***
	(−19.76)	(−19.76)	(−20.10)	(−21.25)	(−22.77)	(−20.95)	(−15.50)	(−18.86)
log(Age$_t$)	0.010***	0.010***	0.010***	0.009***	0.006***	0.006***	0.011***	0.011***
	(7.49)	(7.47)	(7.75)	(6.98)	(4.58)	(3.38)	(4.58)	(6.42)
log(Maturity$_t$)	−0.007***	−0.007***	−0.006***	−0.006***	−0.010***	−0.014***	−0.007***	−0.007***
	(−7.17)	(−7.21)	(−6.02)	(−5.70)	(−11.89)	(−11.06)	(−3.56)	(−6.44)
Low_Liq	−0.002	−0.002	−0.002	−0.004**	−0.001	0.001	−0.000	−0.004**
	(−1.04)	(−1.15)	(−1.08)	(−2.05)	(−0.32)	(0.65)	(−0.13)	(−1.97)
Quarter FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.065	0.067	0.085	0.095	0.175	0.131	0.117	0.220
N of Obs	51,234	51,234	51,234	51,234	51,234	34,698	16,449	28,725

Table VII: **Evidence of Imitation Trading**

This table reports the decomposition of the correlation between institutional demand for corporate bonds and lagged institutional demand between 1998:Q3–2014:Q3. $q_{i,t}$ is the standardized fraction of institutional investors buying bond i in quarter t, with zero mean and unit variance. We estimate quarterly cross-sectional regressions of $q_{i,t}$ on $q_{i,t-1}$. The regression coefficients are also the correlation between institutional demand and lag institutional demand. The second column reports the time-series average of R^2 associated with these quarterly regressions. The third column reports the time-series average of these correlation coefficients and associated t-statistics in parentheses. The last two columns report the portion of the correlation that results from institutional investors following their own lagged trades and the portion that results from institutions following the previous trades of other institutions, defined in Equation (B.3) and Equation (B.4). Panels A, B, and C limit the sample to bonds with at least 1, 5, or 10 trades in both quarters (current and lagged), respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

			Average Partitioned Coefficient β_t	
Type of Trader	Average R^2	Average Coefficient β_t	Following Self	Following Others
Panel A: Bonds with 1 or more traders				
All	0.103	0.261***	0.053***	0.208***
		(25.09)	(8.50)	(34.60)
Mutual Fund	0.052	0.170***	−0.012**	0.182***
		(15.38)	(−2.14)	(24.03)
Pension Fund	0.034	0.133***	−0.022***	0.155***
		(11.14)	(−3.22)	(18.33)
Insurance Company	0.099	0.263***	0.085***	0.178***
		(18.27)	(9.20)	(24.03)
Panel B: Bonds with 5 or more traders				
All	0.175	0.333***	0.014***	0.319***
		(33.60)	(6.19)	(38.12)
Mutual Funds	0.139	0.279***	0.017***	0.262***
		(17.53)	(4.09)	(18.72)
Pension Funds	0.135	0.267***	0.009***	0.258***
		(15.62)	(2.81)	(16.27)
Insurance Companies	0.182	0.343***	0.019***	0.324***
		(23.42)	(6.67)	(25.66)
Panel C: Bonds with 10 or more traders				
All	0.199	0.337***	0.011***	0.326***
		(33.30)	(6.37)	(36.30)
Mutual Funds	0.144	0.280***	0.015***	0.265***
		(20.57)	(5.03)	(21.55)
Pension Funds	0.145	0.252***	−0.000	0.252***
		(6.68)	(−0.06)	(7.13)
Insurance Companies	0.236	0.379***	0.011***	0.368***
		(22.01)	(6.13)	(23.06)

Table VIII: **Institutional Herding and Abnormal Bond Returns**

This table reports abnormal quarterly returns (in percent) on zero-investment portfolios constructed based on bonds' herding measures. Bonds' abnormal return is computed as the raw quarterly return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, financial/nonfinancial classification, and time to maturity. Over the 1998:Q3–2014:Q3 sample period, in each quarter we sort bonds with at least five active trades into quintiles based on their buy (sell) herding measures. Bonds bought with higher intensity than the market average are sorted into quintile "B1" to "B5," with "B5" representing the group of bonds with the highest buy herding measures. Bonds sold with higher intensity than the market average are sorted into quintile "S5" to "S1," with "S5" representing the group of bonds with the highest sell herding measures. Zero-investment portfolio S5-B5 is constructed in a contrarian manner, long the equal-weighted portfolio containing bonds that institutional investors most strongly sold as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that institutional investors most strongly bought as a herd (i.e., B5). Portfolios S5-S1 and B1-B5 are similarly defined. The abnormal quarterly returns on these zero-investment portfolios are reported four quarters before the portfolio formation and six quarters after. In panel B, we report abnormal quarterly returns on portfolio S5-B5 for bond subgroups. A "small" bond is a bond whose outstanding amount is in the bottom two size quintiles in a quarter. An "illiquid" bond is a bond whose overall liquidity measure is in the bottom two liquidity quintiles. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Quarterly Abnormal Return on Zero-Investment Portfolios (in Percent)

Portfolio	$t-4$	$t-3$	$t-2$	$t-1$	Portfolio Formation Quarter t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
S5-B5	−0.67***	−0.84***	−1.03***	−1.11***	−0.44**	0.52**	0.90***	0.28*	0.10	0.28	0.33
S5-S1	−0.48***	−0.73***	−0.69***	−0.75***	−0.00	0.86***	0.97***	0.25*	0.05	0.36*	0.22
B1-B5	−0.09*	−0.15**	−0.32***	−0.43***	−0.37***	−0.35***	−0.06	0.07	0.01	−0.07	0.11

Panel B: Quarterly Abnormal Return on Portfolio S5-B5 (in Percent), for subgroups of bonds

Portfolio & Bond Type	$t-4$	$t-3$	$t-2$	$t-1$	Portfolio Formation Quarter t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
S5-B5: All Bond	−0.67***	−0.84***	−1.03***	−1.11***	−0.44**	0.52**	0.90***	0.28*	0.10	0.28	0.33
S5-B5: High-Yield	−1.53***	−1.96***	−2.32***	−2.71***	−1.34***	1.24**	2.14***	0.63*	0.50*	0.55	0.62
S5-B5: Small	−1.00***	−1.25***	−1.21***	−1.35***	−0.47*	0.75*	1.13***	0.63*	0.15	0.41	0.76*
S5-B5: Illiquid	−1.25***	−1.40***	−1.34***	−1.32***	−0.03	1.50**	1.06**	0.01	0.39	0.30	1.87**