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Institutional herding and its price impact: Evidence from the corporate bond market☆

Fang Cai, Song Han[1], Dan Li, Yi Li*

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ABSTRACT

We examine the extent to which institutional investors herd in the U.S. corporate bond market and the price impact of their herding behavior. We find that the level of institutional herding in corporate bonds is substantially higher than what is documented for equities, and that sell herding is much stronger and more persistent than buy herding. The price impact of herding is also highly asymmetric. While buy herding facilitates price discovery, sell herding causes transitory yet large price distortions. Such price destabilizing effect of sell herding is particularly pronounced for speculative-grade, small, and illiquid bonds, and during the financial crisis.

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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; Financial Stability Oversight Council, 2015). Two recent trends in the US corporate bond market have intensified such concerns. On the one hand, this market has expanded rapidly since the crisis, boosted by significant increases in institutional holdings.[2] On the other hand, over

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* Corresponding author.

E-mail address: yi.li@frb.gov (Y. Li).

[1] Deceased April 2017. This paper is dedicated to the memory of Song Han, who was a wonderful coauthor, colleague and friend.

[2] Based on estimates from the Securities Industry and Financial Markets Association (SIFMA), the US corporate bond market was $7.8 trillion as of the end of 2014. According to the Financial Accounts of the United States, about three-quarters of US corporate bonds, including foreign bonds issued in the US, are held by institutional investors.

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the same time period, corporate bond dealers have sharply shrunk their balance sheets, which may limit their capacity to make the markets (Stein, 2014; Adrian et al., 2015; Bessembinder et al., 2018).

As such, a surge in simultaneous buying or selling caused by institutional herding could potentially 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).[3] Such herding behavior by institutions, when combined with end-investor outflows induced by bad fund performance, could generate a downward spiral on asset prices, and amplify financial stability risks.

Against this backdrop, we address two key empirical questions in this paper: Do institutional investors herd in the corporate bond market? If so, does institutional herding destabilize bond prices? Our focus is on the correlated bond trades by institutions, rather than the redemption runs by end-investors, which are studied in Chen et al. (2010) and Goldstein et al. (2017).[4]

In doing so, we fill a gap in the literature on institutional herding, because most of the existing studies have focused on the equity market, where the level of institutional herding is generally low (except for small stocks and among growth funds), and evidence on the price impact of herding is mixed. For example, Lakonishok et al. (1992) and Wermers (1999) find little herding by pension funds or mutual funds in stocks, but report higher herding in small stocks.[5] Earlier papers find no evidence of price reversals after herding (Nofsinger and Sias, 1999; Wermers, 1999; and Sias, 2004), but papers that focus on more recent time periods do (Sharma et al., 2006; Brown et al., 2014); and (Dasgupta et al., 2011). In contrast, we find a high level of institutional herding in corporate bonds and an even higher level of herding in speculative-grade bonds. We also document a strong price destabilizing effect of such herding on the sell side, represented by a return reversal of about 4% for all bonds in the six quarters after herding, and 6% to 8% for speculative-grade, small, and illiquid bonds.

Taking advantage of a comprehensive data set on U.S. corporate bond holdings by institutional investors, we conduct a thorough analysis of institutional herding and its price impact in the U.S. corporate bond market. First, we estimate the magnitude of institutional herding based on the widely used measure introduced by Lakonishok et al. (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 herding directions. 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 dynamics around herding, which also sheds light on the underlying motives of herding.

Importantly, we conduct our analyses 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 constraints and redemption policies. As such, we compare the prevalence of herding behaviors and its price impact across these investor types within a unified setting, and also explore the ways different types of investors interact with each other.

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, particularly among bonds with lower ratings, and that sell herding is generally stronger than buy herding.[6] Specifically, we estimate the average bond herding levels of pension funds and mutual funds each at about 0.1, significantly higher than the levels of about 0.03 for the respective type of equity funds.[7] Insurance companies, the largest holder of corporate bonds, have an even greater tendency to herd than mutual funds and pension funds, boasting an average herding level of 0.13. Moreover, insurance companies' strong herding tendency holds even after excluding those "fallen angel" bonds that they may have to dispose of due to regulatory constraints.[8]

Further, we also find that the herding level in speculative-grade bonds is notably higher than that in investment-grade bonds. 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.

Second, we find that institutional investors herd more on lower-rated, smaller-sized, more illiquid bonds, and bonds that have recently experienced rating changes. Perhaps unsurprisingly, insurance companies react more after rating changes, particularly after downgrades, consistent with the fact that they are subject to rating-based regulatory constraints. We find some evidence that mutual funds take advantage of such market frictions to buy downgraded bonds when insurance companies are forced to sell them.

[3] 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 to the shock and a subsequent reversal.

[4] Chen et al. (2010) and Goldstein et al. (2017) document the "bank-run" type of behavior among investors of bond mutual funds. 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 et al. (2010) find evidence of such strategic behavior among investors of corporate bond mutual funds. Goldstein et al. (2017) find that corporate bond mutual funds' outflows (i.e., investors' redemptions) react to bad fund performance more than their inflows to good performance.

[5] For more papers on institutional herding in the equity market, see, for example, Froot et al. (1992), Hirshleifer et al. (1994), Hirshleifer and Hong Teoh (2003), Sias (2004); and Brown et al. (2014).

[6] These results hold for a wide variety of robustness checks.

[7] The average herding levels for equity pension funds, estimated by Lakonishok et al. (1992), and the average herding levels for equity mutual funds, estimated by Wermers (1999) and Brown et al. (2014), are in the range of 0.02 to 0.03.

[8] Ellul et al. (2011) document that regulatory constraints imposed on insurance companies can induce fire sales of corporate bonds downgraded from investment-grade to speculative-grade (i.e., fallen angels).

All three types of investors herd to buy winning bonds and herd to sell losing bonds, with insurance companies' herding behavior most sensitive to bonds' past performance. Interestingly, this herding-to-performance relationship is nonlinear. 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 large amount of simultaneous sales from institutional investors, which could lead to further price declines and more sales, resulting in a downward price spiral. Our nonlinear herding-to-performance results echo findings by Goldstein et al. (2017), who show that bond mutual funds' outflows are more sensitive to bad performance than their inflows to good performance. Jointly these results suggest that both fund managers and end-investors are disproportionally sensitive to bad past performance.

To address the natural question whether institutional herding in trading corporate bonds, particularly herding among mutual funds, is driven by fund managers' passive responses to investor flows (as in Coval and Stafford, 2007), we explore how much additional explanatory power mutual fund investor flows have for herding. In general, we find that investor flows explain only a small portion of buy herding by mutual funds, and more importantly, investor flows have little explanatory power for sell herding after we control for bond characteristics and past performances. Therefore, herding in our study mainly reflects active trading behaviors of the fund managers, rather than passive reactions to investor flows.

Third, we document strong persistence in herding, especially on the sell side, and that the persistence is mainly driven by mimicking behavior. 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 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 previous quarter). We find that, interestingly, the positive intertemporal correlation in bond trading is mostly driven by institutions following others' trades. This finding is in stark contrast with what was documented for 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.

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 adjustments that facilitate price discovery, sell herding results in transitory yet significant price distortions and therefore excess price volatility. 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 4% in the six quarters following portfolio formation. Such an abnormal return is entirely driven by subsequent return reversals in bonds that experience heavy sell herding in the event quarter. This evidence is consistent with what Dasgupta et al. (2011) and Brown et al. (2014) find in the equity market, but the price impact of bond herding is much greater in magnitude.

We also find that the price destabilizing effect of sell herding is particularly strong for speculative-grade, small, and illiquid bonds, and during the recent global financial crisis. Specifically, the contrarian portfolio described above generates a cumulative abnormal return of 8% if constructed with speculative-grade bonds, 6% with small bonds, and 7% with less liquid bonds, in the six quarters following portfolio formation. If we focus on the 2007–2009 financial crisis period, the price destabilizing effect reaches as high as 15%. Our results clearly point to the vulnerabilities associated with institutional sell herding in the corporate bond market, i.e., the price-destabilizing effect is the strongest for the most risky bonds during periods of market distress.

Overall, our findings suggest that institutional herding is a key source of fragility as well as a channel of risk amplification in the corporate bond market, distinct from those associated with bond fund investor flows (Chen et al., 2010; Goldstein et al., 2017), and broader in scope than those attributable to downgrade-induced fire sales by regulatory-constrained insurance companies (Ellul et al., 2011).

We perform a series of robustness checks on our main findings. Our empirical findings on the level of herding are robust to alternative definitions of herding. More importantly, results on price impact of herding are robust to alternative measures of herding and various calculation of abnormal returns. In addition, all results remain qualitatively unchanged after removing "fallen angel" events from the sample.

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 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, distinguished by their predictions on price dynamics. In the first group of the models, investors ignore their private information, usually rationally, and imitate others' behavior. Such herding behavior generally results in market inefficiency and excess price volatility. The underlying mechanism may include imperfect information (i.e., information cascades), reputational concern, and benchmark-based compensation structures.[9] In contrast, in the second group of models, investors' trading decisions are driven by fundamentals and their herding behavior expedites 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.[10]

Existing research has well recognized that it is in general very difficult to empirically identify the exact source of the observed herding behavior.[11] Nonetheless, empirical results on the price impact of herding may help identify the motives along the above dichotomy, as suggested by Scharfstein and Stein (1990). That is because most imitational herding models predict price distortions and subsequent price reversals.[12] In contrast, fundamental-driven herding tends to facilitate price discovery and stabilize the market.

In this regard, our study suggests that the motives of institutional herding in corporate bond trading may be mixed. 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.[13] However, papers using more recent stock market data find some price-destabilizing effects of institutional herding, especially on the sell side.[14] 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. Our 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.

Third, we add to the emerging literature on the trading behavior of institutional investors in the corporate bond market. While institutional investor behavior has been a central topic of the asset management literature, most of the studies focus on equity investors.[15] As data became more available, recent studies have explored a number of aspects of corporate bond investor behaviors. For examples, Chen et al. (2010) 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 in corporate bonds, and Manconi et al. (2012) and Ellul et al. (2011) study the fire-sale behavior of bond mutual funds and insurance companies, respectively. We complement the literature by providing a comprehensive analysis on the correlated trading behavior of three major types of institutional investors of corporate bonds—mutual funds, insurance companies, and pension funds. Importantly, we show that our strong evidence on institutional herding is not driven by passive reactions to investor flows, nor by forced sales from regulation-constrained insurance companies. Rather, our results reflect active trading decisions made by institutional investors.

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, as in Becker and Ivashina (2015) and Manconi et al. (2012) among others. This data set is survivorship-bias free, and contains quarter-end security-level corporate bond holdings for insurance companies, mutual funds, and pension funds, which we interchangeably refer to as "funds," "investors," or "institutions" throughout the paper. A detailed discussion on the eMAXX data set is in Appendix A. 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 obtain bond pricing data from the Bank of America Merrill Lynch (ML) Corporate Bond Index Database, as in Acharya et al. (2013) and Schaefer and Strebulaev (2008) among others. The ML database contains daily quoted prices for a representative pool of U.S. public corporate bonds, starting from 1997. Compared to Trade Reporting and Compliance Engine (TRACE), a database that

[9] For models of imperfect information, see Banerjee (1992), Bikhchandani et al. (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).

[10] For models of investigative herding, see Froot et al. (1992), Hirshleifer et al. (1994), Devenow and Welch (1996). For models of characteristics-driven herding, see Falkenstein (1996), Del Guercio (1996), Bennett et al. (2003).

[11] See, for example, Bikhchandani and Sharma (2000) for discussions on the challenges.

[12] 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.

[13] See Lakonishok et al. (1992), Froot et al. (1992), Hirshleifer et al. (1994), Wermers (1999), and Sias (2004).

[14] See Sharma et al. (2006), Dasgupta et al. (2011), and Brown et al. (2014).

[15] See, for example, Brown et al. (1996), Chevalier and Ellison (1997), Coval and Stafford (2007).

provides transaction prices of corporate bonds, the ML data provide a longer and more balanced sample of bond prices.[16] Dealer quotes provided by ML are reflective of actual transaction prices. A comparison between ML quoted prices and TRACE transaction prices for the period after the implementation of TRACE suggests that the ML quoted price tracks the last trade price of the day closely. Detailed information on the ML pricing data set is also in Appendix A.

In addition to the institutional holding data obtained from eMAXX and the bond pricing data provided by Merrill Lynch, we also use the Fixed Investment Securities Database (FISD) to complement information on bond characteristics, the transaction data from TRACE to calculate bond liquidity measures, and the Center for Research in Security Prices (CRSP) Survivor-Bias-Free US Mutual Fund Database to calculate mutual fund investor flows.

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 and held by U.S. institutional investors.[17] We use this full sample to examine the data coverage and overall investor composition.

Starting from the full sample, we impose further restrictions to form our "herding sample"— the sample that will be used in our calculation of institutions' herding levels. 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.[18] About two-thirds of this "herding sample" is matched with pricing information from the ML database.[19]

3.2. Sample statistics

We first examine our data coverage using the full sample. As shown in Panel 1a of Fig. 1, from 1998:Q3 to 2014:Q3, the total number of institutions have increased from about 4000 to nearly 6000, driven mainly by the rapid growth in bond mutual funds (Investment Company Institute, 2016). We also find that while the total number of bonds held by institutions, shown in Panel 1b, is roughly steady at about 30,000, the dollar value of these holdings, shown in Panel 1c of Fig. 1, 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

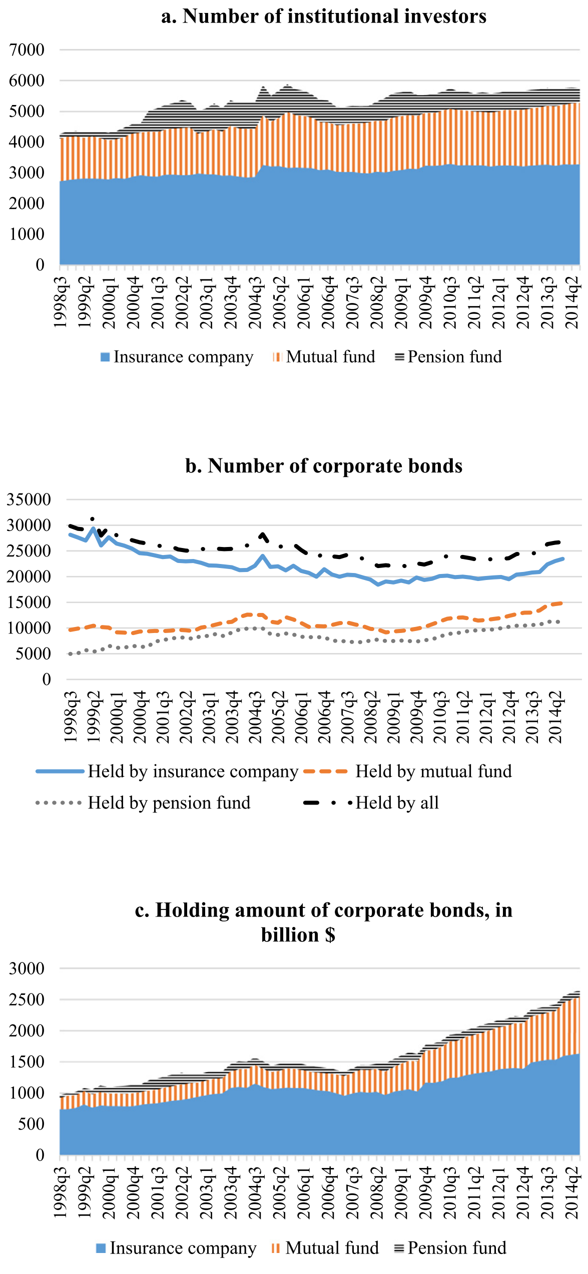

Fig. 1. eMAXX Coverage on institutional holdings of corporate bonds. This figure plots the time series of eMAXX data coverage on institutional holdings of corporate bonds between 1998:Q3 and 2014:Q3, broken down into three institutional investor types: insurance companies, mutual funds, and pension funds. All other institutional investors in eMAXX, whose holdings make up about 1% of total observations, are excluded. Fig. 1a plots the time series of the number of institutional investors by type, excluding foreign funds. Fig. 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. Fig. 1c plots the time series of the dollar value of corporate bonds held by eMAXX investors (in billions).

[16] In 2002, the Financial Industry Regulatory Authority started to require its member dealers to report their secondary market transactions to TRACE. Therefore, TRACE reports the transaction price of a bond whenever it is being traded.

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

[18] 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.

[19] In terms of number of observations, 68% of the "herding sample" is matched with pricing information from the ML database. In terms of amount outstanding, 85% is matched.

Table 1
Summary statistics.
Panel A of this table provides summary statistics for corporate bond holdings of an average eMAXX institutional investor, broken down into three investor types. In the "Holding" columns, we average total dollar values and numbers of corporate bonds across all funds and all quarters. 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. We then average the number of trades across all funds and all quarters. In the "Percentage of portfolio traded" columns, we define $Sales_{i,t} = \sum_j Amount\ Sold_{i,j,t} / \sum_j Amount\ Held_{i,j,t-1} \times 100$ and $Purchase_{i,t} = \sum_j Amount\ Bought_{i,j,t} / \sum_j Amount\ Held_{i,j,t-1} \times 100$, where $Amount Sold(Bought)_{i,j,t}$ is the net par amount of bond j sold (bought) by fund i in quarter t, and $Amount\ Held_{i,j,t-1}$ is the par amount of bond j held by fund i at the end of quarter $t-1$. We then average the percentage of traded portfolios across all funds and all quarters. Panel B provides summary statistics for an average corporate bond held by eMAXX investors, broken down into two risk levels. Bonds with fewer than five trades in a given quarter are excluded. In the "Bond characteristics" columns, we average amount outstanding (in million \$), bond age, and time-to-maturity across all bonds and all quarters. 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 the "Quarterly trades" columns, for each bond in each quarter, we count the number of institutions that sell and buy that bond, respectively. We then average the number of sellers and buyers. Bonds issued or maturing within one year are excluded from both panels.

Panel A: Summary statistics of an average investor

Type of investors	Holding		Quarterly trades		Percentage of portfolio traded	
	Holding amount (in million \$)	Number of bonds held	Number of sales	Number of purchases	Sales (in percent)	Purchase (in percent)
All	312	96	10	7	11	15
Insurance company	361	94	7	4	9	12
Mutual fund	264	94	14	11	16	20
Pension fund	179	106	13	8	14	16

Panel B: Summary statistics of an average bond

Type of bonds	Bond characteristics			Holding information		Quarterly trades	
	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	546	4	9	70	203	11	8
Investment-grade	634	5	10	87	265	10	9
High-yield	414	4	7	60	146	14	9

expansion of the corporate bond market.[20] Notably, mutual funds have substantially increased the amount of bonds held in their portfolios over time, and their market shares among these three types of institutions have risen from 19% to 34%.

Panel A of Table 1 characterizes institutional holdings and trading activities for an average eMAXX investor.[21] In particular, an average institution holds 96 bonds worth \$312 million at a quarter-end, actively buys seven bonds and sells ten bonds in a quarter, with active purchases taking up 15% of its portfolio value and active sales 11%.[22] By investor type, mutual funds and pension funds are significantly more active in trading than insurance companies, both in terms of number of trades and shares of portfolios. Of note, on average, mutual funds are the most active traders of corporate bonds.

Panel B of Table 1 presents summary statistics of a typical bond in our sample, excluding bonds that are issued or maturing within one year. In particular, an average bond has an outstanding amount of \$546 million—of which \$203 million is held by 70 investors in our sample—is about four years after issuance, and has nine years remaining to maturity. On average, it is "actively" sold by 11 institutions and bought by eight institutions in a quarter. Compared with high-yield bonds, investment-grade bonds tend to be larger and have longer time to maturity, and are more widely held by institutional investors. As for trading intensity, a high-yield bond is on average sold more frequently than an investment-grade bond.

3.3. Herding measures

Following the existing literature, we adopt the herding measure proposed by Lakonishok et al. (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 $\mathrm{E}[p_{i,t}]$ with the

[20] Throughout the sample period, the total institutional holdings of bonds covered by our data have 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.

[21] For more summary statistics by time period, see our Online Appendix.

[22] Active purchases or sales refer to trades of bonds that are issued at least one year ago and at least one year from maturity.

market-wide intensity of buying denoted as $\overline{p}_t$. 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 Eq. (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.[23] The second term in Eq. (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 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 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 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.[24] 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.

Another way to measure herding is to use the amount of purchases (in dollars) and sales, rather than the number of purchases and sales. Adapted from Lakonishok et al. (1992) and Wermers (1999), our dollar-based herding measure is defined as

$$DHM_{i,t} = \frac{|\text{Buy Amount}_{i,t} - \text{Sell Amount}_{i,t}|}{\text{Buy Amount}_{i,t} + \text{Sell Amount}_{i,t}}. \tag{3.6}$$

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

$$DBHM_{i,t} = DHM_{i,t}, \text{ if Buy Amount}_{i,t} > \text{Sell Amount}_{i,t}, \tag{3.7}$$

and

$$DSHM_{i,t} = DHM_{i,t}, \text{ if Buy Amount}_{i,t} < \text{Sell Amount}_{i,t}. \tag{3.8}$$

Unlike the LSV herding measure, this dollar-ratio trade imbalance measure does not adjust for market trend in a given quarter. Still, it serves as a good alternative when looking at the price impact of institutional herding. For most of the paper, we report the results using the standard LSV measure, as Sias et al. (2006) find evidence that count-based measures are better predictors of stock returns than dollar-based measures.

4. Empirical results on herding

In this section, we estimate the level of institutional herding in corporate bonds and study the determinants of both sell herding and buy herding. We also 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 their herding behaviors may vary under different regulatory environments and redemption policies.

4.1. Levels of herding

We first examine the level of institutional herding in trading corporate bonds and how it varies by investor type and bond credit rating. The results are summarized in Tables 2 and 3. Following Lakonishok et al. (1992), we require that bonds are traded by at least five institutions in a given quarter.[25] The level of institutional herding in corporate bonds is high. As shown in Table 2, the mean herding measure for all institutions together is about 0.11. 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.

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

[24] 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.

[25] 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.

Table 2
Herding measures (in percent) of corporate bond investors, by investor type.
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. 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)	11.10***	(251,765)	9.65***	(139,771)	8.62***	(50,356)	13.18***	(139,264)
	BHM	(2)	9.80***	(135,364)	8.43***	(76,293)	9.06***	(24,481)	13.34***	(73,153)
	SHM	(3)	12.28***	(116,401)	10.82***	(63,478)	7.83***	(25,874)	12.52***	(66,110)
	BHM-SHM	(4)	−2.49***		−2.39***		1.23***		0.82***	
≥ 10	HM	(5)	11.40***	(156,781)	9.98***	(77,397)	9.35***	(17,248)	15.19***	(58,531)
	BHM	(6)	9.90***	(88,366)	8.55***	(43,647)	9.36***	(8,418)	14.28***	(30,133)
	SHM	(7)	13.16***	(68,415)	11.67***	(33,750)	9.19***	(8,830)	15.93***	(28,398)
	BHM-SHM	(8)	−3.25***		−3.13***		0.17		−1.65***	
≥ 20	HM	(9)	11.69***	(79,482)	10.84***	(30,119)	10.27***	(3,264)	18.11***	(16,857)
	BHM	(10)	9.78***	(45,337)	8.50***	(16,623)	9.37***	(1,622)	15.90***	(7925)
	SHM	(11)	14.14***	(34,145)	13.67***	(13,496)	11.08***	(1,642)	20.00***	(8932)
	BHM-SHM	(12)	−4.35***		−5.18***		−1.71***		−4.10***	
≥ 30	HM	(13)	12.10***	(45,271)	12.07***	(14,283)	11.46***	(859)	20.98***	(6638)
	BHM	(14)	9.78***	(25,644)	8.76***	(7,607)	9.57***	(429)	18.61***	(2798)
	SHM	(15)	15.07***	(19,627)	15.80***	(6,676)	13.25***	(430)	22.67***	(3840)
	BHM-SHM	(16)	−5.29***		−7.05***		−3.67***		−4.06***	

Table 3
Herding measures (in percent) of corporate bond investors, by investor type and bond rating.
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. 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 1–2 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. 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.

# of Active trades	Herding measure	All eMAXX investors: Investment grade (1)	High yield (2)	Mutual funds: Investment grade (3)	High yield (4)	Pension funds: Investment grade (5)	High yield (6)	Insurance companies: Investment grade (7)	High yield (8)
≥ 5	HM	8.83***	11.54***	7.91***	10.59***	7.61***	8.89***	10.88***	14.62***
	BHM	8.75***	10.16***	7.62***	8.87***	8.74***	8.96***	11.86***	15.75***
	SHM	8.54***	12.61***	8.00***	11.93***	6.06***	8.47***	8.71***	13.29***
	BHM-SHM	0.21***	−2.45***	−0.38***	−3.06***	2.68***	0.49***	3.15***	2.46***
≥ 10	HM	9.65***	11.78***	8.36***	10.82***	8.36***	9.54***	13.04***	16.73***
	BHM	9.06***	10.35***	7.89***	8.88***	9.50***	9.07***	12.88***	16.81***
	SHM	10.44***	13.12***	9.02***	12.59***	7.00***	9.84***	12.96***	16.52***
	BHM-SHM	−1.37***	−2.77***	−1.13***	−3.70***	2.50***	−0.77***	−0.08	0.28
≥ 20	HM	10.51***	11.99***	9.34***	11.43***	8.77***	10.53***	16.51***	19.92***
	BHM	9.17***	10.10***	7.98***	8.61***	9.62***	9.02***	14.70***	18.49***
	SHM	12.67***	13.91***	11.55***	14.19***	7.73***	11.89***	18.45***	20.65***
	BHM-SHM	−3.50***	−3.81***	−3.58***	−5.58***	1.89**	−2.87***	−3.76***	−2.16***
≥ 30	HM	11.08***	12.34***	10.61***	12.54***	9.30***	12.15***	19.76***	22.27***
	BHM	9.35***	9.95***	8.41***	8.66***	10.00***	9.19***	17.67***	20.31***
	SHM	13.89***	14.79***	13.97***	16.15***	7.97***	14.39***	21.62***	22.97***
	BHM-SHM	−4.54***	−4.84***	−5.56***	−7.49***	2.04	−5.20***	−3.95***	−2.66**

The results on the levels of herding are robust to our choice of the minimum number of institutions trading on the bond. In fact, the level of herding increases substantially as more institutions trade on a bond, driven by increasing herding on the sell side. This finding contrasts 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.

The level of herding varies by investor type. Insurance companies, the largest investor group for corporate bonds, exhibit the greatest tendency to herd, with an average herding measure of 0.13.[26] The herding measures for mutual funds and pension funds are also fairly high, at around 0.1 and 0.09, respectively. 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 et al. (1992) find that the average level of herding in stocks by pension funds is 0.027, much lower than our finding of 0.086 for bond pension funds, as shown in Column 5. Wermers (1999) and Brown et al. (2014) document that the average level of herding in stocks by equity mutual funds is 0.034 and 0.033, respectively, also substantially lower than our finding of 0.097 for bond mutual funds, as shown in Column 3.

We also find that sell herding is generally much stronger than buy herding, particularly so for mutual funds. For pension funds and insurance companies, herding is stronger on the buy side when we require at least five active trades. The result for mutual funds is consistent with existing findings in the equities market. For examples, Wermers (1999) and Brown et al. (2014) find relatively 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. 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.

Herding is stronger among risker bonds. Table 3 shows that the mean herding measure is 8.8 and 11.5 for investment-grade and speculative-grade bonds, respectively. We find similar patterns for each type of investors.

As Ellul et al. (2011) find, regulatory constraints imposed on insurance companies can induce fire sales of corporate bonds downgraded from investment-grade to speculative-grade. To test how much this regulatory effect contributes to our measure of institutional herding, we repeat the calculation in Table 2 while excluding all "fallen angels."[27] After such exclusion, the average buy herding measure is almost unchanged, while the sell herding measure decreases slightly from 0.123 to 0.121.[28]

Table 4 reports dollar-based herding measures. Consistent with our results based on the LSV measure, the level of institutional herding in corporate bonds based on trading volume is also very high. Specifically, the dollar-based herding measure for all investors averages at 0.58. This number implies that if the total trading amount of a given bond is \$100, \$79 will be on one side of the market, and \$21 will be on the other side. Also consistent with our findings based on the LSV measure, sell herding is much stronger than buy herding, and this imbalance between sell herding and buy herding increases as more institutions trade on a bond.[29]

4.2. 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 suggest that institutional herding is related to their positive-feedback trading strategies (see Grinblatt et al., 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 strategy exists for the corporate bond market, and, if so, whether this herding-performance relationship is linear.

We calculate quarterly raw returns on corporate bonds 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

$$r_{i,t} = \frac{(P_{i,t+1} + I_{i,t+1}) - (P_{i,t} + I_{i,t}) + D_{i,t} \times C_{i,t} \times (1 + r_{Libor,t})^{\Delta t}}{P_{i,t} + I_{i,t}}, \quad (4.1)$$

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, industry sector, and time

[26] We repeat all tests separately for life insurers and non-life insurers (such as property and casualty insurers), and obtain qualitatively similar results.

[27] A corporate bond is defined as a "fallen angel" in quarter t if it has been downgraded from investment-grade to non-investment grade in quarter t or quarter $t-1$, as it usually takes weeks or months for insurance companies to divest these downgraded bonds.

[28] For full details on herding measures calculated without "fallen angels," see our Online Appendix.

[29] We perform additional robustness checks on the herding measure results. To address the concern that herding is driven by correlated trading among funds managed by the same firm, we compute the average LSV herding measure at the managing firm level to be 0.08, a little lower than the fund-level measure but still fairly high, suggesting herding is prevalent even at the managing firm level. We also find evidence that institutions have a tendency to herd in industry sectors. These results are reported in our Online Appendix.

Table 4
Dollar-based herding measures of corporate bond investors.
This table reports mean dollar-based 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 dollar-based herding measure (DHM) is defined as the dollar-ratio trade imbalance between buying and selling. Following Lakonishok et al. (1992) and Wermers (1999), $DHM_{i,t} = |Buy\ Amount_{i,t} - Sell\ Amount_{i,t}|/(Buy\ Amount_{i,t} + Sell\ Amount_{i,t})$. Dollar-based buy (sell) herding measure is defined as $DBHM_{i,t}(DSHM_{i,t}) = DHM_{i,t}$, if $Buy\,Amount_{i,\,t} > (<) Sell\,Amount_{i,\,t}$. Column 1 of this table presents the mean of $DHM_{i,\,t}$, $DBHM_{i,\,t}$, and $DSHM_{i,\,t}$, 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 $DHM_{i,\,t}$, $DBHM_{i,\,t}$, and $DSHM_{i,\,t}$ all recalculated within each subgroup. We also compute the difference between the mean of $DBHM_{i,\,t}$ and $DSHM_{i,\,t}$ 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	DHM	0.58***	(247,004)	0.62***	(139,771)	0.64***	(50,356)	0.66***	(139,264)
	DBHM	0.50***	(133,987)	0.58***	(58,504)	0.55***	(18,113)	0.57***	(52,514)
	DSHM	0.63***	(113,017)	0.65***	(80,631)	0.69***	(32,228)	0.71***	(86,373)
	DBHM-DSHM	−0.12***		−0.07***		−0.14***		−0.14***	
≥ 10	DHM	0.52***	(153,516)	0.56***	(77,397)	0.56***	(17,248)	0.62***	(58,531)
	DBHM	0.44***	(87,371)	0.51***	(31,840)	0.46***	(5968)	0.51***	(21,096)
	DSHM	0.57***	(66,145)	0.59***	(45,496)	0.62***	(11,278)	0.68***	(37,419)
	DBHM-DSHM	−0.13***		−0.08***		−0.16***		−0.18***	
≥ 20	DHM	0.47***	(77,620)	0.51***	(30,119)	0.51***	(3264)	0.62***	(16,857)
	DBHM	0.38***	(44,751)	0.44***	(11,627)	0.39***	(1056)	0.47***	(5654)
	DSHM	0.53***	(32,869)	0.55***	(18,474)	0.57***	(2208)	0.69***	(11,203)
	DBHM-DSHM	−0.15***		−0.11***		−0.17***		−0.22***	
≥ 30	DHM	0.45***	(44,140)	0.49***	(14,283)	0.51***	(859)	0.64***	(6638)
	DBHM	0.35***	(25,280)	0.41***	(5371)	0.38***	(271)	0.47***	(2067)
	DSHM	0.51***	(18,860)	0.54***	(8909)	0.57***	(588)	0.71***	(4571)
	DBHM-DSHM	−0.16***		−0.13***		−0.19***		−0.24***	

to maturity in that quarter (see Appendix B for the detailed benchmark methodology).

Second, we include bond characteristics such as size, 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 et al. (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 in corporate bonds is related to trading liquidity.

Last but not least, we examine the persistence of herding behavior by including indicators on herding directions in past quarters. If herding in a particular bond persists after controlling for publicly observable bond characteristics, it may imply either imitation behavior or autocorrelation of self-trading, which we will explore in depth in Section 4.5.

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

$$\begin{aligned} &BHM_{i,t}(\text{or, } SHM_{i,t}) \\ &= \alpha_{i,t} + \sum_{\tau=1}^{4}\beta_\tau RET_{i,t-\tau} + \sum_{\tau=1}^{2}\lambda_\tau RET^2_{i,t-\tau} \\ &\quad + \sum_{\tau=0}^{1}\left(\gamma^U_\tau UpGd_{i,t-\tau} + \gamma^D_\tau DownGd_{i,t-\tau}\right) \\ &\quad + \sum_{\tau=1}^{2}\left(\phi^B_\tau BHD_{i,t-\tau} + \phi^S_\tau SHD_{i,t-\tau}\right) + \delta LIQ_i \\ &\quad + \sum_k \theta_k Character^k_{i,t} + FE\epsilon_{i,t}. \qquad (4.2) \end{aligned}$$

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 nonlinearity in the sensitivity of herding behavior to past returns. $UpGd_{i,t-\tau}$ is a dummy variable that equals one if there is an upgrade for bond i during quarter $t-\tau$ and equals zero otherwise. Similarly, $DownGd_{i,t-\tau}$ is a dummy variable that equals one 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.[30] Finally, we use quarter and issuer fixed effects to control for unobservable heterogeneity over time and across issuers.[31]

We conduct additional analyses to check the robustness of our results. In reported results, standard errors are clustered at the individual bond level. Results are not

[30] For a full list of these independent variables and the details about how they are calculated, see Appendix B.

[31] Brown et al. (2014) find an important role for analyst recommendation revisions in driving herding in stocks. To investigate the role of analyst revisions in driving herding in corporate bonds, we collect the analyst recommendation data from Thomson Reuters' Institutional Brokers' Estimate System (I/B/E/S) and run similar tests as in Brown et al. (2014). In general, our results show that the effects of analyst revisions on corporate bond herding are smaller, less significant, and more mixed than those on equity herding. Two reasons may help explain this fact. First, in addition to analyst recommendations, corporate bonds also receive independent credit ratings from several rating agencies like Moody's and Standard & Poor's (S&P), which also change over time and may dilute the information content of analyst recommendations. Second, it is worth noting that the I/B/E/S recommendations generally target equity investors, and mainly reflect analysts' views of the valuation of stocks. For detailed discussions and regression results, see our Online Appendix.

Table 5
Determinants of buy herding levels.
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. 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, sector, and time to maturity in quarter $t-\tau$. Upgrade$_{t-\tau}$ (Downgrade$_{t-\tau}$) is a dummy that equals one if there is an upgrade (downgrade) of ratings in quarter $t-\tau$ and equals zero 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 $t-\tau$. For example, BHD = 0 and SHD = 1 if the bond is sold with higher intensity than the market average and traded by at least five funds. Inv_Grade$_t$ equals one if the bond is investment-grade and zero otherwise. Low_Liq equals one 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. For details about the calculation of independent variables, see Appendix B. 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, in percent								
	All					Mutual fund	Pension fund	Insurance company
	(1)	(2)	(3)	(4)	(5)			
Ab_Ret$_{t-1}$	4.462***	5.393***	5.168***	5.615***	4.839***	3.357***	7.638***	−0.746
	(5.64)	(6.82)	(6.56)	(7.06)	(5.81)	(3.36)	(4.23)	(−0.40)
Ab_Ret$_{t-2}$	3.353***	4.028***	3.754***	4.739***	4.149***	3.619***	0.456	4.372**
	(5.06)	(5.38)	(5.04)	(6.30)	(5.26)	(3.80)	(0.26)	(2.32)
Ab_Ret$_{t-3}$	2.466***	2.394***	2.194***	2.365***	1.726**	0.880	2.029	3.373**
	(3.69)	(3.57)	(3.30)	(3.55)	(2.49)	(1.04)	(1.40)	(2.29)
Ab_Ret$_{t-4}$	1.125	1.142	0.974	1.089	0.609	−0.520	−3.118**	2.014
	(1.58)	(1.61)	(1.39)	(1.53)	(0.79)	(−0.64)	(−2.07)	(1.16)
Ab_Ret$^2_{t-1}$		−0.736**	−0.650*	−0.716**	−0.709***	−0.506*	−1.567***	1.063**
		(−2.13)	(−1.90)	(−2.14)	(−2.65)	(−1.88)	(−4.07)	(2.08)
Ab_Ret$^2_{t-2}$		−0.643**	−0.573**	−0.901***	−0.883***	−0.558**	−0.115	−6.279
		(−2.47)	(−2.12)	(−3.90)	(−3.60)	(−2.03)	(−0.12)	(−1.04)
Upgrade$_t$	0.028	0.025	0.053	0.121	0.117	−0.246	−0.122	0.162
	(0.18)	(0.16)	(0.34)	(0.75)	(0.70)	(−1.13)	(−0.28)	(0.53)
Upgrade$_{t-1}$	0.304*	0.299*	0.319*	0.238	0.234	−0.015	0.122	1.208***
	(1.79)	(1.76)	(1.88)	(1.39)	(1.31)	(−0.06)	(0.25)	(3.89)
Downgrade$_t$	−0.388**	−0.381**	−0.362**	−0.192	−0.333**	−0.037	0.520	−1.185***
	(−2.53)	(−2.49)	(−2.38)	(−1.22)	(−2.02)	(−0.17)	(1.23)	(−4.04)
Downgrade$_{t-1}$	0.123	0.137	0.130	0.087	−0.091	0.680***	0.933**	−1.329***
	(0.77)	(0.86)	(0.81)	(0.53)	(−0.53)	(3.00)	(2.08)	(−4.61)
BHD$_{t-1}$			0.029	−0.270*	−0.296*	−1.760***	−1.174***	−0.244
			(0.18)	(−1.65)	(−1.70)	(−8.58)	(−3.34)	(−1.16)
BHD$_{t-2}$			−0.709***	−0.710***	−0.650***	−1.880***	−1.602***	−0.854***
			(−5.47)	(−5.43)	(−4.72)	(−11.10)	(−5.07)	(−4.56)
SHD$_{t-1}$			−1.606***	−1.944***	−1.766***	−3.629***	−4.007***	−1.814***
			(−9.38)	(−11.04)	(−9.49)	(−16.19)	(−10.46)	(−7.23)
SHD$_{t-2}$			−1.307***	−1.362***	−1.146***	−2.039***	−1.964***	−1.789***
			(−8.88)	(−9.19)	(−7.40)	(−10.75)	(−5.37)	(−7.38)
Inv_Grade$_t$	−0.359***	−0.363***	−0.634***	−0.658***	−1.010***	−0.549	0.159	−1.045**
	(−3.16)	(−3.20)	(−5.49)	(−5.64)	(−3.89)	(−1.57)	(0.25)	(−2.17)
log(Size$_t$)	−0.854***	−0.852***	−0.680***	−0.685***	−0.474***	−0.223	−1.521***	−1.067***
	(−12.99)	(−12.96)	(−9.69)	(−9.58)	(−4.11)	(−1.37)	(−3.97)	(−5.21)
log(Age$_t$)	0.039	0.041	0.087	0.030	0.138	1.018***	0.996***	−1.569***
	(0.50)	(0.52)	(1.09)	(0.37)	(1.44)	(7.85)	(3.16)	(−9.67)
log(Maturity$_t$)	0.946***	0.945***	0.877***	0.873***	0.980***	0.289***	1.201***	2.182***
	(15.23)	(15.23)	(14.29)	(14.24)	(14.76)	(3.30)	(4.79)	(17.99)
Low_Liq	0.760***	0.760***	0.747***	0.728***	0.498***	0.262	1.279***	0.332
	(7.04)	(7.05)	(6.98)	(6.82)	(3.99)	(1.56)	(3.42)	(1.55)
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	0.013	0.027	0.088	0.141	0.183	0.152
N of Obs	92,964	92,964	92,964	92,964	92,964	57,243	18,444	50,259

affected by either clustering standard errors at the quarter level or double-clustering at the bond-quarter level. Also, in reported regressions, our sample includes bonds actively traded by at least five investors in a given quarter. Our main results remain robust if we require at least ten active trades.

4.2.1. Determinants of buy herding

Table 5 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 1–5, the coefficients on bonds' abnormal returns in the previous three 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 do not find evidence that top-performing bonds attract disproportionally larger herds. In fact, Columns 2–5 of Table 5 report a strong 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 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 strongly 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, likely taking advantage of market frictions created by regulations that insurance companies are subject to. We further explore interactions of trading among different types of investors in Section 4.4.

Herding in previous quarters affects 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 et al. (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 6, we present the regression results for sell herding. Comparing R^2 results in Table 6 with those in Table 5, we find that the same set of independent variables has 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 6, 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 all types of investors have a long memory of bond performance when forming selling herds.

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 selloffs 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 145 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 116 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 6, experiencing selling herds in the previous two quarters corresponds to a combined 223 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 even after controlling for publicly observable fund characteristics.

Other bond characteristics also contribute to explaining sell herding. First, insurance companies and mutual funds herd more to sell speculative-grade bonds than investment-grade bonds, while pension funds do the opposite. 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, bond liquidity does not seem to play a significant role in sell herding after controlling for other factors.

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 performance leads 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.

4.3. Is mutual fund herding driven by investor flows?

A natural question to ask is whether institutional herding is driven by fund managers' passive responses to investor flows rather than by their active decisions. eMAXX only provides information on holdings of fixed-income

Table 6
Determinants of sell herding levels.
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, sector, and time to maturity in quarter $t-\tau$. $Upgrade_{t-\tau}$ ($Downgrade_{t-\tau}$) is a dummy that equals one if there is an upgrade (downgrade) of ratings in quarter $t-\tau$ and equals zero 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 $t-\tau$. For example, BHD = 0 and SHD = 1 if the bond is sold with higher intensity than the market average and traded by at least five funds. Inv_Grade_t equals one if the bond is investment-grade and zero otherwise. Low_Liq equals one 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. For details about the calculation of independent variables, see Appendix B. 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, in percent							
	All					Mutual	Pension	Insurance
	(1)	(2)	(3)	(4)	(5)	fund	fund	company
Ab_Ret_{t-1}	−4.969***	−7.683***	−6.942***	−6.474***	−6.173***	−3.054***	−3.304**	−4.718***
	(−6.04)	(−9.47)	(−8.60)	(−8.08)	(−7.34)	(−2.71)	(−2.19)	(−4.09)
Ab_Ret_{t-2}	−3.813***	−5.284***	−4.173***	−4.191***	−3.781***	−3.422***	−4.141**	−2.855**
	(−4.10)	(−6.00)	(−4.77)	(−4.76)	(−4.20)	(−2.83)	(−2.40)	(−2.21)
Ab_Ret_{t-3}	−3.311***	−2.779***	−1.984**	−1.969**	−2.822***	−2.117**	−2.865**	−1.453
	(−3.72)	(−3.22)	(−2.37)	(−2.37)	(−3.23)	(−1.99)	(−2.15)	(−1.20)
Ab_Ret_{t-4}	−2.990***	−2.598***	−1.752*	−1.727*	−2.013**	−2.613**	−1.609	−5.560***
	(−3.17)	(−2.79)	(−1.93)	(−1.93)	(−2.11)	(−2.41)	(−1.11)	(−3.74)
$Ab\_Ret^2_{t-1}$		6.745***	6.199***	5.585***	4.385***	2.760*	1.949	1.428***
		(4.04)	(3.93)	(3.64)	(2.71)	(1.84)	(0.90)	(3.66)
$Ab\_Ret^2_{t-2}$		5.731***	4.877***	4.836***	3.174***	−0.647	0.903**	0.157
		(4.51)	(4.27)	(4.20)	(3.12)	(−0.59)	(2.17)	(0.47)
$Upgrade_t$	0.254	0.230	0.179	0.392*	0.363*	0.480*	1.026***	0.259
	(1.26)	(1.14)	(0.90)	(1.94)	(1.76)	(1.80)	(2.87)	(0.81)
$Upgrade_{t-1}$	1.214***	1.213***	1.167***	1.202***	1.162***	0.990***	0.321	0.936***
	(5.79)	(5.79)	(5.67)	(5.75)	(5.38)	(3.51)	(0.86)	(2.99)
$Downgrade_t$	0.685***	0.607***	0.611***	0.902***	0.579***	0.544**	0.715**	0.678***
	(3.89)	(3.46)	(3.52)	(5.01)	(3.08)	(2.08)	(2.02)	(2.63)
$Downgrade_{t-1}$	1.951***	1.800***	1.680***	1.857***	1.452***	1.473***	0.489	1.619***
	(10.56)	(9.83)	(9.24)	(9.93)	(7.53)	(5.40)	(1.32)	(6.88)
BHD_{t-1}			−0.187	−0.763***	−0.145	−0.334	−0.395	−0.395*
			(−0.98)	(−3.79)	(−0.75)	(−1.36)	(−1.40)	(−1.91)
BHD_{t-2}			−0.357**	−0.410***	−0.009	0.116	−0.681***	0.388**
			(−2.37)	(−2.64)	(−0.06)	(0.54)	(−2.64)	(2.04)
SHD_{t-1}			2.484***	1.927***	1.564***	1.064***	1.309***	0.904***
			(10.68)	(8.11)	(7.64)	(4.19)	(4.64)	(4.02)
SHD_{t-2}			1.399s***	1.299***	0.668***	0.515**	0.561**	1.445***
			(6.58)	(6.07)	(3.71)	(2.27)	(1.99)	(6.40)
Inv_Grade_t	−3.826***	−3.700***	−3.020***	−2.704***	−1.569***	−0.824**	1.332***	−3.341***
	(−23.15)	(−22.25)	(−17.97)	(−15.79)	(−5.60)	(−2.12)	(2.65)	(−8.85)
$\log(Size_t)$	−1.643***	−1.640***	−1.777***	−1.978***	−3.086***	−3.776***	−3.198***	−2.954***
	(−18.04)	(−18.04)	(−18.72)	(−20.02)	(−22.17)	(−20.79)	(−15.03)	(−18.22)
$\log(Age_t)$	1.070***	1.066***	1.040***	0.959***	0.488***	0.526***	1.079***	0.961***
	(7.66)	(7.63)	(7.99)	(7.35)	(4.01)	(2.95)	(4.56)	(5.93)
$\log(Maturity_t)$	−0.739***	−0.741***	−0.619***	−0.589***	−1.044***	−1.439***	−0.660***	−0.746***
	(−7.20)	(−7.24)	(−6.15)	(−5.79)	(−12.18)	(−11.29)	(−3.54)	(−6.59)
Low_Liq	−0.179	−0.193	−0.168	−0.344**	−0.062	0.199	0.060	−0.340
	(−1.00)	(−1.08)	(−0.99)	(−1.98)	(−0.39)	(0.88)	(0.21)	(−1.62)
Quarter FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.061	0.063	0.079	0.091	0.236	0.214	0.236	0.299
N of Obs	50,897	50,897	50,897	50,897	50,897	34,770	16,553	28,560

securities of each fund, rather than total net assets (TNA) of each fund. To calculate investor flows, we need to explore other data sources. Given the fact that insurance companies and pension funds in general do not experience significant unexpected investor flows, we focus our effort on mutual funds. As pointed out by Chen et al. (2010), mutual funds with illiquid assets (i.e., bond mutual funds) exhibit stronger sensitivity of outflows to bad past performance than funds with liquid assets, and this “bank run” type of behavior can pose risks on financial stability.

The CRSP Survivor-Bias-Free US Mutual Fund Database includes information on TNA and returns on bond mutual funds. Following the literature, we define fund k's percentage flow during quarter t as

$$flow_{k,t} = \frac{TNA_{k,t} - TNA_{k,t-1} \times (1 + R_{k,t})}{TNA_{k,t-1}} \times 100, \qquad (4.3)$$

where $R_{k,t}$ is the return on fund k in quarter t and $TNA_{k,t}$ is the TNA of fund k at the end of quarter t. If fund managers herd in passive responses to investor flows, we would expect that they increase or decrease their holdings of each bond in proportion to investor flows. To measure the investor flow associated with a particular corporate bond i for our bond-level regression, we define

$$flow_{i,t} = \frac{\sum_{k=1}^{K}(flow_{k,t} \times holding_{k,i,t})}{\sum_{k=1}^{K} holding_{k,i,t}}, \tag{4.4}$$

where $holding_{k,\, i,\, t}$ is the holding amount of bond i by fund k at the end of quarter t.[32]

We include $flow_{i,\, t}$ as an additional explanatory variable to our regressions of the determinants of herding measures, and report results in Table 7. The sample is restricted to mutual funds. We cluster standard errors by bond, and control for quarter-fixed effects and issuer-fixed effect. Columns 1–3 show results on buy herding measures, and Columns 4–6 show results on sell herding measures.

Column 1 of Table 7 shows that the estimated coefficient on $flow_{i,\, t}$ bears a positive sign, significant at 1% level. This estimate is economically significant as well, as an increase of investor flows by 10% is associated with 105 basis point increase in the level of buy herding, after controlling for bonds' performance, past herding directions, and other bond characteristics. To further disentangle the effects of inflows versus outflows, Columns 2 and 3 report regression results by requiring $flow_{i,\, t} > 0$ and $flow_{i,\, t} < 0$, respectively. The estimated coefficients remain positive and are both significant at 1% level. Specifically, an inflow of 10% corresponds to an 88 basis point increase in the level of buy herding, and an outflow of 10% corresponds to a 173 basis point decrease in the level of buy herding. These results suggest that for corporate bonds that are bought more intensively than the market average, the negative effect exerted by outflows on buy herding is larger than the positive effect generated by inflows, after controlling for other variables.

As for sell herding, Column 4 of Table 7 shows that the estimated coefficient on $flow_{i,\, t}$ bears a negative sign, but has very little explanatory power for the sell herding measure, and is very small in magnitude. To test for any asymmetric effects of inflows and outflows on sell herding, in Columns 5 and 6 we report regression results by requiring $flow_{i,\, t} > 0$ and $flow_{i,\, t} < 0$, respectively. The estimated coefficients remain negative and statistically insignificant.

In general, we show that mutual fund flows are positively associated with buy herding, and negatively associated with sell herding (although not significant). Even though the effect of mutual fund flows on buy herding is significant, it only explains a small portion of the high herding level of bond mutual funds. More importantly, mutual fund flows have little explanatory power for sell herding, after controlling for other variables and fixed effects. Therefore, we can rule out the possibility that institutional herding is driven by fund managers' passive responses to investor flows.

For robustness, we replace $flow_{i,\, t}$ with $flow_{i,t-1}$ and repeat all regressions in Table 7. We do so to test for any lagged effects of mutual fund investor flows on herding levels. We find no evidence of such lagged effects.

4.4. Who bought downgraded bonds sold by insurers?

In Section 4.2, we find that rating changes have different effects on insurance companies than on mutual funds and pension funds. One potential reason is that because of regulatory constraints, insurance companies are more sensitive to bond downgrades, especially to downgrades from investment-grade to non-investment grade. As argued by Ellul et al. (2011), insurance companies who are constrained by regulations are more likely to divest these "fallen angels" and potentially trigger fire sales.

Our sample allows us to look into potential interactions across different types of institutions, especially when insurance companies sell downgraded bonds. Specifically, we estimate the following models:

$$\begin{aligned} &Mutual(Pension)\ Fund\ Net\ Trade_{i,t} = Insurer\ Net\ Trade_{i,t} \\ &+ Insurer\ Net\ Trade_{i,t} \times Downgraded_{i,t}(Fallen_{i,t}) + FE_t. \end{aligned} \tag{4.5}$$

Table 8 reports regression results on the interactions among different types of corporate bond investors, when insurance companies sell bonds. We compute the net trading amount of a certain bond in each quarter by institution type. We only look at cases when insurance companies are net sellers of the bond, either in quarter t, as in Columns 1–2 and 5–6, or in quarter $t-1$, as in Columns 3–4 and 7–8. $Downgraded_{i,\, t}$ is a dummy variable that equals one when bond i is downgraded in quarter t or quarter $t-1$, and zero otherwise. $Fallen_{i,\, t}$ is a dummy variable that equals one when bond i is downgraded from investment-grade to non-investment grade (i.e., a "fallen angel") in quarter t or quarter $t-1$, and zero otherwise. We cluster standard errors at the bond (CUSIP) level and control for quarter-fixed effects.

The dependent variable in Columns 1–4 is mutual funds' net trading amount of bond i in quarter t. Regression results show that when a bond without recent downgrades is on net sold by insurance companies, it is also more likely to be sold by mutual funds. Specifically, Column 1 shows that \$100 more of sales of a downgrade-free corporate bond by insurance companies is associated with \$11 more sales by mutual funds, significant both statistically and economically. However, if the bond has been downgraded in the recent two quarters, \$100 more sales of that bond by insurance companies is associated with only \$5 more sales by mutual funds, as indicated by the estimate on the interaction term in Column 1. In other words, downgrades reduce the positive correlation between insurers' sales and mutual funds' sales by half. More strikingly, the estimates in Column 2 show that for a "fallen angel," \$100 more sales of that bond by insurance companies is actually associated with \$6 more purchases by mutual funds, significant at the 1% level. This result suggests that drastic downgrades from investment-grade to non-investment grade could overturn the trading dynamics between insurers and mutual funds.

Given the fact that it may take more than a quarter for other investors to pick up what insurance companies sell,

[32] Following the literature, we winsorize $flow_{i,\, t}$ at the top and bottom 1% levels to account for mergers and splits. Our results remain robust with the change of winsorization range.

Table 7
Is mutual fund herding driven by investor flows?
This table reports results of regressing buy (sell) herding measures on mutual fund flows, controlling for other variables. The dependent variable is the buy (sell) herding measure of bond i in quarter t calculated within the sample of mutual funds. Fund flows associated with bond i in quarter t are calculated as the average investor flow across all mutual funds who hold bond i, weighted by their holding amount of bond i. Specifically, in quarter t, suppose K mutual funds have holdings of bond i. Denote fund k's holding position of bond i as $holding_{k,\,i,\,t}$. Define fund k's percentage flow as $flow_{k,t} = (TNA_{k,t} - TNA_{k,t-1} \times (1 + R_{k,t}))/TNA_{k,t-1}$, where $R_{k,\,t}$ is the return on fund k in quarter t and $TNA_{k,\,t}$ is the total net assets (TNA) of fund k at the end of quarter t. The fund flow measure associated with bond i is $flow_{i,t} = \sum_{k=1}^{K}(flow_{k,t} \times holding_{k,i,t})/\sum_{k=1}^{K} holding_{k,i,t}$. Other independent variables are defined the same way as in Table 5 and Table 6. "Bond controls" include investment-grade dummy, low-liquidity dummy, logarithm of bond size, logarithm of bond age, and logarithm of time to maturity. For the details about how independent variables are calculated, see Appendix B. 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: BHM			Dependent variables: SHM		
		Flow > 0	Flow < 0		Flow > 0	Flow < 0
	(1)	(2)	(3)	(4)	(5)	(6)
Flow_t	0.105***	0.088***	0.173***	−0.035	−0.017	−0.068
	(5.80)	(3.50)	(2.73)	(−1.54)	(−0.49)	(−0.85)
Ab_Ret_{t-1}	2.647**	2.376**	−0.725	−2.964**	−2.018	−6.418**
	(2.47)	(2.01)	(−0.25)	(−2.34)	(−1.31)	(−2.25)
Ab_Ret_{t-2}	2.787***	1.707	7.526***	−2.609**	−2.228	−6.021**
	(2.75)	(1.47)	(2.95)	(−1.97)	(−1.40)	(−1.97)
Ab_Ret_{t-3}	0.416	−0.017	0.827	−1.764	−2.694	0.922
	(0.48)	(−0.01)	(0.58)	(−1.54)	(−1.61)	(0.53)
Ab_Ret_{t-4}	−0.421	−0.466	1.770	−3.021***	−5.453***	−1.413
	(−0.50)	(−0.36)	(1.18)	(−2.61)	(−3.31)	(−0.76)
Ab_Ret^2_{t-1}	−0.390	−0.436	21.998***	2.273	0.899	14.351***
	(−1.42)	(−1.56)	(3.86)	(1.37)	(0.63)	(2.86)
Ab_Ret^2_{t-2}	−0.425	−0.373	−0.697	−1.076	−1.904	1.719
	(−1.54)	(−1.55)	(−0.83)	(−0.91)	(−0.68)	(1.15)
Upgrade_t	−0.109	0.248	−0.684*	0.506*	0.443	0.208
	(−0.46)	(0.80)	(−1.68)	(1.77)	(1.15)	(0.43)
Upgrade_{t-1}	0.033	−0.156	0.507	1.184***	1.501***	1.023*
	(0.13)	(−0.47)	(1.21)	(3.89)	(3.69)	(1.92)
Downgrade_t	0.033	0.055	0.013	0.717**	0.959**	0.470
	(0.14)	(0.18)	(0.03)	(2.46)	(2.41)	(0.91)
Downgrade_{t-1}	0.660***	0.673**	0.438	1.651***	1.665***	1.872***
	(2.77)	(2.20)	(1.03)	(5.51)	(4.13)	(3.46)
BHD_{t-1}	−1.969***	−2.195***	−1.672***	−0.249	−0.095	−0.252
	(−8.38)	(−7.62)	(−3.66)	(−0.91)	(−0.26)	(−0.53)
BHD_{t-2}	−1.794***	−1.848***	−1.605***	0.090	0.383	−0.803*
	(−9.66)	(−7.92)	(−4.75)	(0.39)	(1.24)	(−1.93)
SHD_{t-1}	−3.893***	−4.119***	−3.492***	1.127***	1.379***	0.958*
	(−15.38)	(−13.24)	(−7.24)	(4.00)	(3.70)	(1.96)
SHD_{t-2}	−1.880***	−2.094***	−1.433***	0.470*	0.645**	−0.424
	(−9.05)	(−8.05)	(−3.80)	(1.92)	(2.00)	(−0.95)
Bond controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.138	0.161	0.224	0.215	0.250	0.322
N of Obs	48,851	32,016	16,835	29,631	18,576	11,054

in Columns 3–4 we regress mutual fund trading amount on lagged insurer trading amount. Results are similar to those in Columns 1–2, but in greater magnitude. In particular, for a "fallen angel," \$100 more sales of that bond by insurance companies in the previous quarter is associated with around \$15 more purchases by mutual funds, as indicated by the estimates in Column 4. This result suggests that mutual funds not only buy "fallen angels" in the same quarter as insurance companies sell them, but also pick up more in the following quarter.

Columns 5–8 use pension funds' net trading amount as dependent variable. We find a positive relationship between insurers' sales and pension funds' sales, significant at 1% level but small in magnitude. Contrary to our findings with mutual funds, downgrades of bonds appear to be associated with more synchronized sales by pension funds, although not significant in most regressions.

In sum, results in Table 8 indicate that, when a downgraded corporate bond is sold by insurance companies, it triggers significantly more discrepancy in trading between insurers and mutual funds. This is especially true for "fallen angels," whose ratings change from investment-grade to speculative-grade. In particular, mutual funds take up a nontrivial portion of these "fallen angels" in the two quarters following sales by insurance companies. These findings suggest that mutual funds tend to provide some liquidity when insurance companies are forced to sell bonds due to regulation constraints. They may do so to

Table 8
Who bought downgraded bonds sold by insurance companies?
This table reports regression results on the interactive trading between different types of corporate bond investors, when insurance companies sell bonds. "Trade" is measured by net trading amount. For example, *Insurer net trade*$_{i,t}$ = −800 means that on net $ 800 worth of bond *i* is sold by insurers in quarter *t*. All regressions are restricted to the case when *Insurernettrade*$_{i,\,t} < 0$, i.e., when insurance companies are net sellers of a particular bond, either in quarter *t*, as in Columns 1–2 and 5–6, or in quarter $t-1$, as in Columns 3–4 and 7–8. Columns 1–4 report regression results using mutual funds' net trading amount in quarter *t* as dependent variables, and Columns 5–8 report regression results using pension funds' net trading amount in quarter *t* as dependent variables. *Downgraded*$_{i,\,t}$ is a dummy variable that equals one when bond *i* is downgraded in quarter *t* or quarter $t-1$. *Fallen*$_{i,\,t}$ is a dummy variable that equals one when bond *i* is downgraded from investment-grade to non-investment grade (i.e., a "fallen angel") in quarter *t* or quarter $t-1$. Bonds traded by fewer than five investors in a quarter are excluded. Bonds issued or maturing within one year are also excluded. 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.

All regressions are restricted to: Insurer net trade <0								
	Dependent var.: Mutual fund net trade$_{i,\,t}$				Dependent var.: Pension fund net trade$_{i,\,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Insurer net trade$_{i,\,t}$	0.107***	0.094***			0.027***	0.021***		
	(4.42)	(3.97)			(3.89)	(3.89)		
Downgraded$_{i,\,t}$ × Insurer net trade$_{i,\,t}$	−0.053*				0.034*			
	(−1.79)				(1.81)			
Fallen$_{i,\,t}$ × Insurer net trade$_{i,\,t}$		−0.156***				0.053		
		(−2.69)				(1.16)		
Insurer net trade$_{i,t-1}$			0.059***	0.058***			0.017***	0.018***
			(6.40)	(6.38)			(7.22)	(7.48)
Downgraded$_{i,t-1}$ × Insurer net trade$_{i,t-1}$			−0.084***				0.007	
			(−4.05)				(1.05)	
Fallen$_{i,t-1}$ × Insurer net trade$_{i,t-1}$				−0.204***				0.004
				(−3.75)				(0.31)
Quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.019	0.016	0.007	0.008	0.026	0.019	0.011	0.011
N of Obs	121,648	120,278	80,018	80,005	121,648	120,278	80,018	80,005

take advantage of the fire-sale prices induced by insurers' selling herds.[33]

4.5. Persistence in herding and imitation behavior

Our regression results in Section 4.2 show 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.[34] Averaging over all quarters and bonds by their initial sorting, we obtain an empirical probability matrix over adjacent quarters, which we plot in Fig. 2.

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 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 it making the highest sell herding quintile in the next quarter is over 40%, and the chance of it making the second-highest sell herding quintile in the next quarter is almost 30%.

Next, to explore the underlying motives for the intertemporal persistence in corporate bond trading, we follow Sias (2004) to break down the herding persistence into imitation and habit components. Specifically, 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). Table 9 reports the decomposition results for corporate bonds in our sample.[35]

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 five active institutional traders, the correlation between institutional trading in bonds in this quarter and that in the previous quarter averages 0.33, significantly different from zero at the 1% level. This average correlation in bond trading is significantly higher than that in equity trading, which is about 0.2, as reported by Sias (2004). 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

[33] See our Online Appendix for a more general discussion on trading dynamics among institutional investors and an extended analysis on corporate bond dealers' nontrivial role in absorbing selling pressures when institutional investors herd to sell bonds.

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

[35] For full details of our estimation approach, see Appendix C.

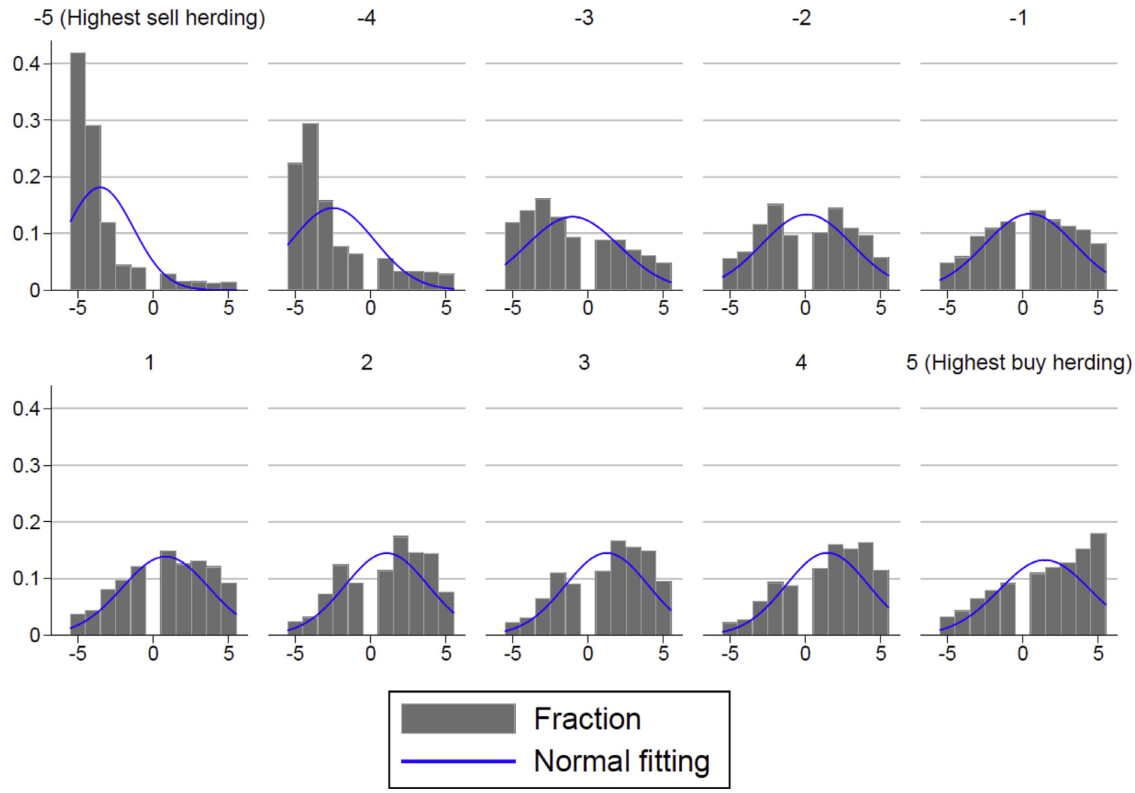

Fig. 2. Persistence of herding over adjacent quarters. This figure plots histograms of future herding levels of bonds based on their current herding levels. Over the 1998:Q3–2014:Q3 sample period, in each quarter we sort bonds with at least five active trades into quintiles based on their buy (sell) herding measures. Bonds bought with higher intensity than the market average are sorted into quintiles "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 quintiles "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.

mutual funds and pension funds. This finding supplements the earlier result that herding within the same quarter is also stronger among 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 a tiny fraction of the intertemporal correlation (i.e., 0.01 out of 0.33) is driven by institutional investors continuing to buy (or sell) the bonds they just bought (or sold) in the previous quarter, while most of the intertemporal correlation (i.e., 0.32 out of 0.33) is driven by investors imitating others' trades in the previous quarter. Similar results hold for all types of investors and for bonds with at least ten traders. These results are in contrast to the findings of Sias (2004), in which the habit factor contributes at least one-third of the persistence in trading stocks.

5. Price impact of herding

Our findings of strong herding in Section 4 raise a key question: Does herding stabilize or destabilize bond prices? In this section, we explore the price impact and stability implications of institutional herding in the corporate bond market. By definition, herding stabilizes prices if herding-associated price changes are permanent, while herding destabilizes prices if herding-associated price changes reverse course. 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), fundamentals-driven herding is generally efficient and facilitates price discovery, while imitation-driven herding is generally inefficient and can lead to price reversals and excess volatilities.

5.1. Price impact: methodology

We use the standard portfolio approach to analyze the return dynamics around institutional herding in the corporate bond market. To study the extent of price reversal (if any) following institutional herding, we examine the relation between herding levels and bond returns in the portfolio formation quarter and the following six quarters. We also look into the relation between herding and past

Table 9
Evidence of imitational 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 Eq. (C.3) and Eq. (C.4). Panels A (B) limit the sample to bonds with at least five (ten) trades in both quarters (current and lagged), respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Type of trader	Average R^2	Average coefficient β_t	Average partitioned coefficient β_t: Following self	Average partitioned coefficient β_t: Following others
Panel A: 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 B: 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)

returns to 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, 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 construct three zero-investment portfolios: S5–B5, S5–S1, and B1–B5, where portfolio S5–B5 represents a zero-investment portfolio that longs bonds with the strongest sell herding intensity (S5) and shorts bonds with the strongest buy herding intensity (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 trend.

We examine the quarterly equal-weighted abnormal returns for each of these contrarian portfolios, before, during, and after the portfolio formation quarter. Following Bessembinder et al. (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 interest) and the average return on a set of bonds with similar credit rating, industry, and remaining term to maturity.[36] 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 importantly, 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 return continuation after portfolio formation would imply that herding facilitates price discovery by impounding new information into bond prices.

We study price impact by bond type, investor type, and economic cycle. In addition, we test the robustness of our results by calculating abnormal bond returns in four alternative ways and replacing the LSV herding measure with the dollar-based herding measure.

5.2. Price impact: results

We study price impact of herding for all bonds together, as well as for three subgroups of corporate bonds: high-yield (speculative-grade) bonds, small bonds, and illiquid

[36] See Appendix B for details on how we calculate the abnormal bond returns.

Table 10
Price impact of herding: by bond type.
This table reports quarterly abnormal returns (in percent) on portfolios constructed based on bonds' herding measures, for four quarters before the portfolio formation quarter t and six quarters after. Bonds' quarterly abnormal return is defined in Appendix B. In each quarter, bonds bought with higher intensity than the market average are sorted into quintiles "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 quintiles "S5" to "S1," with "S5" representing the group of bonds with the highest sell herding measures. Portfolio S5–B5 is long the equal-weighted portfolio containing bonds that institutional investors most strongly sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that institutional investors most strongly buy as a herd (i.e., B5). Portfolios S5–S1 and B1–B5 are similarly defined. This table also reports quarterly 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. Bonds traded by fewer than five investors in a given quarter are excluded. Bonds issued or maturing within one year are also excluded. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Bond type	$t-4$	$t-3$	$t-2$	$t-1$	Portfolio formation quarter t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Panel A: Quarterly abnormal return on portfolio S5–B5 (in percent)											
All	−0.55***	−0.78***	−1.07***	−1.07***	−0.24	0.88***	1.11***	0.76***	0.16	0.31	0.23
High-yield	−1.42***	−1.97***	−2.61***	−2.80***	−1.13***	1.98***	2.66***	1.51***	0.57*	0.69	0.61
Small	−0.84***	−1.21***	−1.25***	−1.27***	−0.25	1.44***	1.56***	1.21***	0.31	0.52	0.42
Illiquid	−1.03***	−1.23***	−1.67***	−1.09**	0.70	2.08***	1.32**	0.75*	0.54	0.52	1.69**
Panel B: Quarterly abnormal return on portfolio S5–S1 (in percent)											
All	−0.40***	−0.63***	−0.65***	−0.64***	0.31*	1.23***	1.12***	0.69***	0.09	0.47*	0.16
High-yield	−1.03***	−1.17***	−1.13***	−1.34***	0.55*	2.80***	2.42***	1.27***	0.39	0.82*	0.41
Small	−0.47***	−0.92***	−0.57***	−0.76***	0.35	1.82***	1.60***	1.11***	0.23	0.63*	0.21
Illiquid	−1.06***	−1.07***	−1.38***	−0.92**	1.11*	2.46***	1.29**	0.62	0.41	0.83**	1.70**
Panel C: Quarterly abnormal return on portfolio B1–B5 (in percent)											
All	−0.08	−0.17***	−0.37***	−0.48***	−0.43***	−0.37***	0.00	0.11**	0.02	−0.07	0.16**
High-yield	−0.20	−0.76***	−1.32***	−1.42***	−1.11***	−0.82***	0.07	0.36**	0.00	−0.05	0.62**
Small	−0.31**	−0.28***	−0.64***	−0.66***	−0.47***	−0.38***	−0.05	0.26**	−0.03	−0.06	0.24**
Illiquid	0.08	−0.07	−0.44***	−0.17*	−0.27***	−0.38***	0.09	0.15	0.09	−0.09	0.07

bonds.[37] Table 10 presents the quarterly abnormal returns around the herding quarters for the three zero-investment portfolios described in Section 5.1.

Panel A of Table 10 reports quarterly abnormal returns on portfolio S5–B5, the most contrarian portfolio based on herding measures. Its contrarian nature is shown by its strongly negative returns in quarters leading up to portfolio formation, all significant at the 1% level. In particular, bonds heavily sold by herds (S5) on average underperform bonds heavily bought (B5) by about 55–107 basis points in terms of quarterly abnormal return in the four quarters prior to portfolio formation. The magnitude of this underperformance of S5 relative to B5 before portfolio formation is substantially larger for the three subgroups of corporate bonds.

More importantly, we find bond returns revert immediately after the portfolio formation quarter for portfolios S5–B5. The abnormal returns on portfolio S5–B5 become positive in the quarter immediately following portfolio formation and remain positive for at least six quarters. The effects of return reversals are larger for high-yield bonds, small bonds, and illiquid bonds.

To disentangle return reversals driven by sell herding from buy herding, in Panel B and Panel C of Table 10 we report quarterly abnormal returns on portfolios S5–S1 and B1–B5, respectively. It shows that a higher level of sell herding (S5 compared to S1) is associated with lower abnormal returns prior to the portfolio formation quarter, and that a higher level of buy herding (B5 compared to B1) is associated with higher past abnormal returns. These results suggest that positive-feedback trading strategies contribute to both buy and sell herding.

In terms of post-herding price dynamics, we find significant asymmetry between sell herding and buy herding. On the sell side, the abnormal returns on portfolio S5–S1 go from negative to positive even in the portfolio formation quarter and remain positive for at least six additional quarters. On the buy side, however, the abnormal returns on portfolio B1–B5 continue to be strongly negative in the quarter immediately following portfolio formation and largely diminish afterward. Results of portfolio returns on S5–S1 and B1–B5 for the three subgroups of bonds also show that return reversals are mainly driven by sell herding. The strong return reversals following sell herding suggest that institutional sell herding destabilizes corporate bond prices, and the return continuation following buy herding suggests that buy herding helps price discovery and stabilizes prices.

For better illustration, we plot in Fig. 3 cumulative abnormal returns, instead of quarterly abnormal returns, on portfolios S5–B5, S5–S1, and B1–B5, constructed with the full sample as well as subgroups of bonds. The cumulative abnormal return is indexed to zero at the end of the portfolio formation quarter t. For the full sample, the

[37] 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 detail in Appendix B.

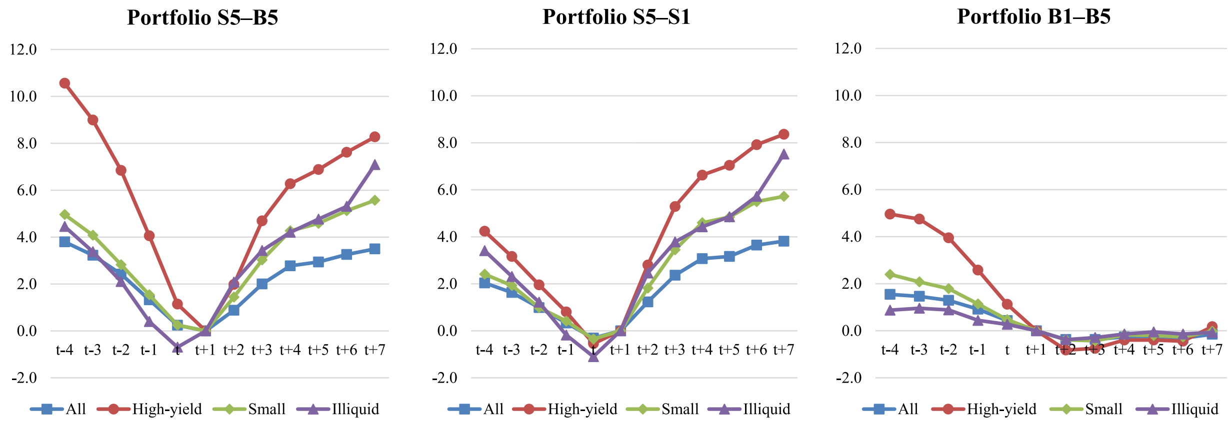

Fig. 3. Price impact of institutional herding, by bond type. This figure illustrates cumulative abnormal returns (in percent) on zero-investment portfolios S5–B5, S5–S1, and B1–B5 before and after portfolio formation quarter *t*. Bonds' quarterly abnormal return is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, industry sectors, and time to maturity. (See Appendix B.) The cumulative abnormal return is indexed to zero at the end of the portfolio formation quarter *t*. In each quarter, bonds bought with higher intensity than the market average are sorted into quintiles "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 quintiles "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 sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that institutional investors most strongly buy 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. Bonds traded by fewer than five investors in a given quarter are excluded. Bonds issued or maturing within one year are also excluded.

S5–B5 portfolio loses 4% in the four quarters leading up to portfolio formation quarter *t* but earns an abnormal return of near 4% within six quarters afterward. We find that both positive-feedback trading strategies before portfolio formation and return reversals after portfolio formation are much stronger for subgroups of bonds. For high-yield bonds, the return reversal is strongest, with a cumulative abnormal return of 8% on portfolio S5–B5 in six quarters after portfolio formation. Small bonds and illiquid bonds display similar but smaller-in-magnitude patterns, gaining cumulative abnormal returns of 6% and 7% on portfolio S5–B5, respectively.

Fig. 3 also highlights the stark contrast between the cumulative abnormal returns on portfolio S5–S1 and those on portfolio B1–B5 after portfolio formation. While the strong return reversals on portfolio S5–S1 show that sell herding exerts large yet transitory pressure on bond prices, driving the bond prices substantially away from their fundamental values and causing excessive price volatility, the return continuation on portfolio B1–B5 indicates that buy herding speeds up price discovery. This finding suggests that the underlying motives of sell herding and buy herding in the corporate bond market may be different. Sell herding is consistent with imitative trading based on career/reputation concerns, but buy herding is likely driven by fundamentals.

We also look into the price impact of herding by different types of investors. Table 11 presents the quarterly abnormal returns on portfolios S5–B5, S5–S1, and B1–B5 for insurance companies, mutual funds, and pension funds, and Fig. 4 plots corresponding cumulative abnormal returns. The return reversal patterns don't vary much across different institution types, suggesting that herding by all three types of institutions contributes to the price dynamics of bonds.[38] However, it is worth noting that return reversals on portfolios S5–B5 and S5–S1 of insurance companies are more immediate than those of mutual funds and pension funds. In particular, the quarterly abnormal returns on portfolios S5–B5 and S5–S1 of insurance companies turn strongly positive in the quarter immediately after portfolio formation, while they take longer to turn positive for mutual funds and pension funds. This finding suggests that the corporate bonds insurance companies herd to sell are the most undervalued, which tend to experience the most immediate return reversals.

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 Table 12 and Fig. 5, 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.[39]

Not surprisingly, the price reversal patterns in portfolios 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 12% in a few quarters leading up to quarter *t*. As price

[38] The exact price impact of each type of institution is hard to disentangle because of correlated herding in bonds between subgroups of investors. We conduct additional tests (not reported) and find that sell herding across different types of investors is more positively correlated than buy herding.

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

Table 11
Price impact of herding: by investor type.
This table reports quarterly abnormal returns (in percent) on portfolios constructed based on bonds' herding measures of investor subgroups, for four quarters before the portfolio formation quarter t and six quarters after. Bonds' quarterly abnormal return is defined in Appendix B. Within each subgroup of investors (insurance company, mutual fund, or pension fund), in each quarter, bonds bought with higher intensity than the market average are sorted into quintiles "B1" to "B5," with "B5" representing the group of bonds with the highest subgroup buy herding measures. Bonds sold with higher intensity than the market average are sorted into quintiles "S5" to "S1," with "S5" representing the group of bonds with the highest subgroup sell herding measures. Portfolio S5–B5 is long the equal-weighted portfolio containing bonds that the subgroup of investors most strongly sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that the subgroup of investors most strongly buy 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. Bonds issued or maturing within one year are also excluded. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Investor type	$t-4$	$t-3$	$t-2$	$t-1$	Portfolio formation quarter t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Panel A: Quarterly abnormal return on portfolio S5–B5 (in percent)											
Mutual fund	−0.47***	−0.65***	−0.72***	−1.14***	−0.94***	−0.08	1.31***	0.90***	0.68***	0.02	0.55**
Pension fund	−0.24	−0.96***	−1.03***	−1.50***	−0.53**	−0.38	1.33***	1.00***	0.17	0.11	0.65
Insurance company	−0.36**	−0.30*	−0.65***	−1.35***	−0.69	0.93***	1.20***	1.04***	0.05	0.32*	0.22
Panel B: Quarterly abnormal return on portfolio S5–S1 (in percent)											
Mutual fund	−0.37***	−0.42***	−0.32***	−0.53***	−0.21	0.27	1.38***	0.95***	0.51**	0.05	0.22
Pension fund	−0.24*	−0.68***	−0.72***	−0.52***	0.02	0.02	1.21***	0.94***	0.15	0.43**	0.69*
Insurance company	−0.30**	−0.06	−0.4**	−1.03***	−0.27	1.06***	1.09***	0.94***	0.06	0.31*	0.16
Panel C: Quarterly abnormal return on portfolio B1–B5 (in percent)											
Mutual fund	0.03	−0.17**	−0.40***	−0.53***	−0.62***	−0.37***	0.02	0.02	0.18**	−0.02	0.15*
Pension fund	0.23	−0.31*	−0.15	−0.88***	−0.29**	−0.49***	0.13	0.10	0.24	−0.15	0.14
Insurance company	−0.10*	−0.17**	−0.17***	−0.20***	−0.33***	−0.14**	−0.07	0.04	0.02	0.05	0.13*

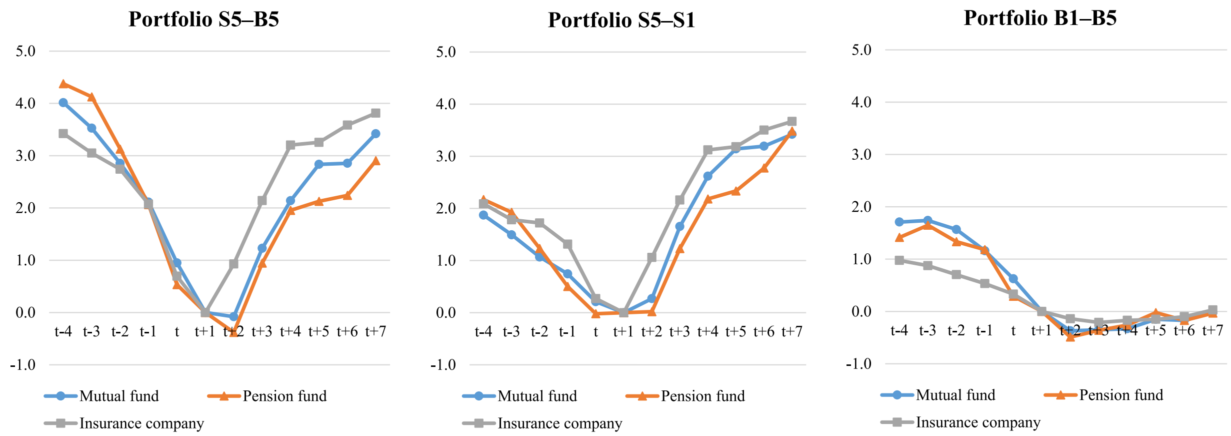

Fig. 4. Price impact of institutional herding, by investor type. This figure illustrates cumulative abnormal returns (in percent) on zero-investment portfolios S5–B5, S5–S1, and B1–B5 constructed based on herding measures of investor subgroups, before and after portfolio formation quarter t. Bonds' quarterly 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, industry sectors, and time to maturity. (See Appendix B.) The cumulative abnormal return is indexed to zero at the end of the portfolio formation quarter t. 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 quintiles "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 quintiles "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 sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that the subgroup of investors most strongly buy 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. Bonds issued or maturing within one year are also excluded.

pressure dissipates, prices of these bonds revert as much as 15% within six quarters after portfolio formation. In contrast, during normal times, the cumulative abnormal return on portfolio S5–B5 after portfolio formation is less than 2%. Therefore, the price destabilizing effect of sell herding is strongest when the market is under stress and liquidity tends to dry out.

5.3. Price impact: robustness

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

Table 12
Price impact of herding: by economic cycle.
This table reports quarterly abnormal returns (in percent) on portfolios constructed based on bonds' herding measures during the global financial crisis and normal times, for four quarters before the portfolio formation quarter *t* and six quarters after. Bonds' quarterly abnormal return is defined in Appendix B. In each quarter, bonds bought with higher intensity than the market average are sorted into quintiles "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 quintiles "S5" to "S1," with "S5" representing the group of bonds with the highest sell herding measures. Portfolio S5–B5 is long the equal-weighted portfolio containing bonds that institutional investors most strongly sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that institutional investors most strongly buy as a herd (i.e., B5). Portfolios S5–S1 and B1–B5 are similarly defined. Crisis period is defined as 2007:Q3–2009:Q2, and non-crisis periods 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/non-crisis period controls for the spillover effect. Bonds traded by fewer than five investors in a given quarter are excluded. Bonds issued or maturing within one year are also excluded. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Period	$t-4$	$t-3$	$t-2$	$t-1$	Portfolio formation quarter t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Panel A: Quarterly abnormal return on portfolio S5–B5 (in percent)											
All time	−0.55***	−0.78***	−1.07***	−1.07***	−0.24	0.88***	1.11***	0.76***	0.16	0.31	0.23
Crisis	−1.10***	−1.86***	−3.18***	−3.57***	−1.60	4.52***	5.53***	1.64*	0.74	0.82	0.71
Non−crisis	−0.33**	−0.47***	−0.79***	−0.78***	−0.25*	0.16	0.48**	0.65***	−0.04	0.02	0.17
Panel B: Quarterly abnormal return on portfolio S5–S1 (in percent)											
All time	−0.40***	−0.63***	−0.65***	−0.64***	0.31*	1.23***	1.12***	0.69***	0.09	0.47*	0.16
Crisis	−0.89***	−1.65***	−3.58***	−3.68***	0.15	5.88***	5.14***	0.92	−0.27	2.11**	0.36
Non−crisis	−0.08	−0.37***	−0.36***	−0.41***	0.16	0.36*	0.54***	0.63***	0.02	−0.02	0.19
Panel C: Quarterly abnormal return on portfolio B1–B5 (in percent)											
All time	−0.08	−0.17***	−0.37***	−0.48***	−0.43***	−0.37***	0.00	0.11**	0.02	−0.07	0.16**
Crisis	−0.08	−0.22**	0.34**	0.16	−1.45***	−1.34***	0.07	0.40	0.33	−0.64*	0.95**
Non-crisis	−0.21***	−0.09**	−0.33***	−0.46***	−0.28***	−0.21***	−0.01	0.08*	−0.05	0.01	0.02

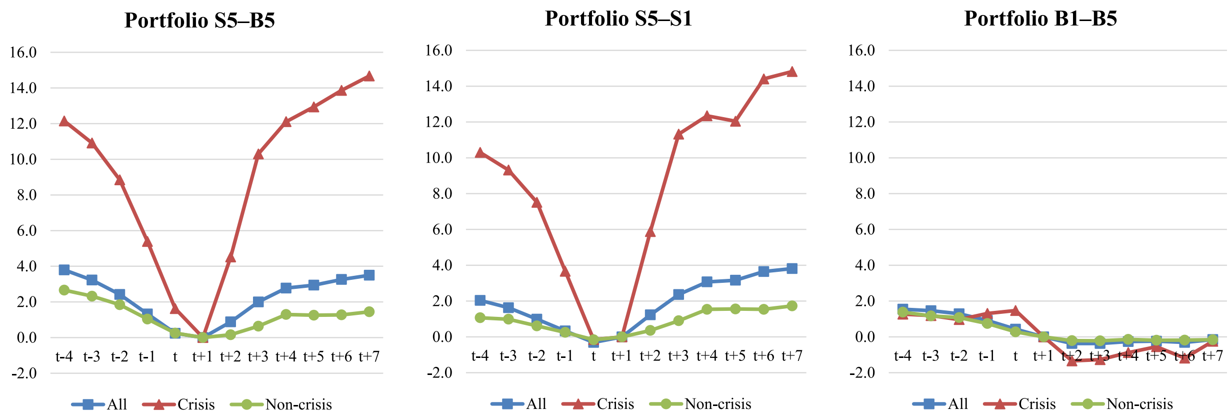

Fig. 5. Price impact of institutional herding, by economic cycle. This figure illustrates cumulative abnormal returns (in percent) on zero-investment portfolios S5–B5, S5–S1, and B1–B5 constructed based on herding measures during the global financial crisis and normal times. Bonds' quarterly abnormal 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, industry sectors, and time to maturity. (See Appendix B.) The cumulative abnormal return is indexed to zero at the end of the portfolio formation quarter *t*. In each quarter, bonds bought with higher intensity than the market average are sorted into quintiles "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 quintiles "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 sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that investors most strongly buy 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. Bonds issued or maturing within one year are also excluded. Crisis period is defined as 2007:Q3–2009:Q2, and non-crisis periods 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/non-crisis period controls for the spillover effect.

(see Lakonishok et al., 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 et al., 2014; Dasgupta et al., 2011), but is much stronger in magnitude.

Given our strong yet novel results on the price impact of institutional herding in corporate bonds, we perform a series of robustness checks, including employing alternative calculation of bond returns, using different definitions of herding measures, and ruling out some alternative explanations.

First, we use four alternative measures of bond returns and repeat the tests on price impact. Table 13 reports quarterly (abnormal) returns on portfolios S5–B5,

Table 13
Robustness on price impact of herding: alternative bond returns.
This table reports quarterly abnormal returns (in percent) on portfolios constructed based on bonds' herding measures, for four quarters before the portfolio formation quarter t and six quarters after. Bonds' quarterly returns are measured in four alternative ways. "Raw return" is defined by Eq. (B.1). "Alternative I" is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings and time to maturity. "Alternative II" is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, time to maturity, and financial/nonfinancial sectors. "5-Factor alpha" is estimated from the five-factor bond model developed in Fama and French (1993): $R_{bond,t} - R_{f,t} = \alpha + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Term_t + \beta_5 Def_t + \varepsilon_t$. In each quarter, bonds bought with higher intensity than the market average are sorted into quintiles "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 quintiles "S5" to "S1," with "S5" representing the group of bonds with the highest sell herding measures. Portfolio S5–B5 is long the equal-weighted portfolio containing bonds that institutional investors most strongly sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that institutional investors most strongly buy as a herd (i.e., B5). Portfolios S5–S1 and B1–B5 are similarly defined. Bonds traded by fewer than five investors in a given quarter are excluded. Bonds issued or maturing within one year are also excluded. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Return type	$t-4$	$t-3$	$t-2$	$t-1$	Portfolio formation quarter t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Panel A: Quarterly return on portfolio S5–B5 (in percent)											
Raw return	−0.50***	−0.69***	−1.35***	−0.81***	0.18	1.70***	1.65***	0.99***	0.58**	0.92***	0.69**
Alternative I	−0.61***	−0.82***	−1.08***	−1.08***	−0.47**	0.53**	0.97***	0.33*	0.03	0.20	0.18
Alternative II	−0.63***	−0.8***	−1.02***	−1.08***	−0.38**	0.57**	0.94***	0.40*	0.05	0.20	0.17
5-Factor alpha	−0.52***	−0.53***	−0.94***	−0.88***	−0.04	1.15***	1.55***	0.82***	0.28	0.69***	0.64***
Panel B: Quarterly return on portfolio S5–S1 (in percent)											
Raw return	−0.03	−0.32**	−0.69***	−0.34*	0.84***	1.99***	1.80***	0.98***	0.70***	1.15***	0.71**
Alternative I	−0.43***	−0.68***	−0.75***	−0.72***	−0.05	0.84***	1.00***	0.27	0.03	0.31	0.17
Alternative II	−0.46***	−0.66***	−0.69***	−0.74***	0.03	0.88***	1.01***	0.35*	0.01	0.30	0.10
5-Factor alpha	−0.14	−0.37***	−0.63***	−0.40***	0.69***	1.71***	1.59***	0.85***	0.40**	0.91***	0.62***
Panel C: Quarterly return on portfolio B1–B5 (in percent)											
Raw return	−0.37***	−0.36***	−0.61***	−0.46***	−0.52***	−0.37***	−0.11*	−0.09	−0.20**	−0.20**	0.02
Alternative I	−0.10*	−0.12**	−0.34***	−0.40***	−0.39***	−0.33***	0.02	0.08*	0.01	−0.07	0.10
Alternative II	−0.10*	−0.13**	−0.31***	−0.40***	−0.36***	−0.33***	−0.01	0.10*	0.02	−0.05	0.11*
5-Factor alpha	−0.27***	−0.13*	−0.43***	−0.48***	−0.50***	−0.47***	−0.05	−0.01	−0.15*	−0.15**	0.07

S5–S1, and B1–B5 before and after portfolio formation, measured in these alternative ways. Specifically, "Raw return" is calculated based on bond prices, adjusted for interest and coupon payments, and defined by Eq. (B.1). "Alternative I" is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings and time to maturity.[40] "Alternative II" is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, time to maturity, and financial/nonfinancial sectors.[41] "5-Factor alpha" is estimated from the five-factor bond model developed in Fama and French (1993) and also used in Bessembinder et al. (2009). Specifically,

$$R_{bond,t} - R_{f,t} = \alpha + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Term_t + \beta_5 Def_t + \varepsilon_t. \quad (5.1)$$

This model is an extension of the three-factor stock return model and adds two additional factors, where $Term_t$ represents the slope of the Treasury yield curve, and Def_t the premium measured as the difference between the returns on the long-term corporate bond index (Merrill Lynch corporate bond index) and long-term Treasuries. In this model, α is estimated to be the abnormal return on each portfolio.[42]

Results in Table 13 show that all of our findings on price impact of herding remain qualitatively unchanged and even much stronger for "Raw return" and "5-Factor alpha," both in magnitude and significance. Specifically, in the six quarters following portfolio formation, raw returns and five-factor alphas on portfolio S5–S1 are all strongly

[40] The credit rating buckets are (AAA, AA, A, BBB, BB, B, C&D). The time to maturity buckets are (1–5 years, 5–10 years, over ten years). Therefore, we have seven rating buckets and three maturity buckets. After interacting these two ways of sorting, we have 21 benchmark bond portfolios in each quarter. To obtain the abnormal return on an individual bond in a given quarter, we calculate the size-weighted average raw returns on those 21 benchmark portfolios and then subtract the corresponding benchmark raw return from the raw return on that individual bond.

[41] The credit rating buckets for financial corporate bonds are (AAA, AA, A, BBB, BB&below). The credit rating buckets for nonfinancial corporate bonds are (AAA&AA, A, BBB, BB, B, C&D). The sector buckets are (financial, nonfinancial). The time to maturity buckets are (1–5 years, 5–10 years, over ten years). Therefore, we have five or six rating buckets (depending on whether the bond is financial or not), two sector buckets, and three maturity buckets. After interacting these three ways of sorting, we have 33 benchmark bond portfolios in each quarter. To obtain the abnormal return on an individual bond in a given quarter, we calculate the size-weighted average raw returns on those 33 benchmark portfolios and then subtract the corresponding benchmark raw return from the raw return on that individual bond.

[42] The five-factor model we use is similar to the four-factor model developed by Elton et al. (1995) and used by Gutierrez et al. (2008) and Cici and Gibson (2012). The four factors include: STK (excess return on the CRSP value-weighted stock index, similar to our first factor, $R_m - R_f$), TERM (difference in return between the Ibbotson and Associates long-term government bond index and their intermediate bond index, similar to *Term* in our model), DEF (return difference of the Lehman High-Yield and Intermediate Government indices, similar to *Def* in our model), and OPTION.

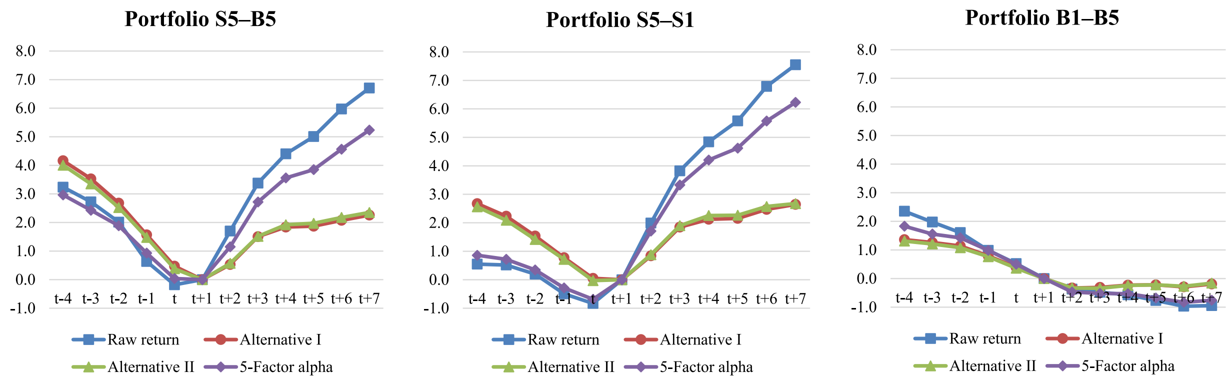

Fig. 6. Robustness on price impact of herding: alternative bond returns. This figure illustrates cumulative returns (in percent) on zero-investment portfolios S5–B5, S5–S1, and B1–B5 before and after portfolio formation quarter *t*, measured in four alternative ways. "Raw return" is calculated based on bond prices, adjusted for interest and coupon payments and defined by Eq. (B.1). "Alternative I" is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings and time to maturity. "Alternative II" is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, time to maturity, and financial/nonfinancial sectors. "5-Factor alpha" is estimated from the five-factor bond return model developed in Fama and French (1993): $R_{bond,t} - R_{f,t} = \alpha + \beta_1 (R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Term_t + \beta_5 Def_t + \varepsilon_t$. This model is an extension of the three-factor stock return model and adds two additional factors, where *Term* represents the slope of the Treasury yield curve, and *Def* the premium measured as the difference between the returns on the long-term corporate bond index (Merrill Lynch corporate bond index) and long-term Treasuries. The cumulative abnormal return is indexed to zero at the end of the portfolio formation quarter *t*. In each quarter, bonds bought with higher intensity than the market average are sorted into quintiles "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 quintiles "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 sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that institutional investors most strongly buy as a herd (i.e., B5). Portfolios S5–S1 and B1–B5 are similarly defined. Bonds traded by fewer than five investors in a given quarter are excluded. Bonds issued or maturing within one year are also excluded.

positive and significant at the 1%–5% level. This solidifies our return reversal results on sell herding. In Fig. 6, we also plot cumulative returns on portfolios S5–B5, S5–S1, and B1–B5, measured in these four alternative ways. It is evident that "Raw return" shows the strongest return reversal pattern in portfolios S5–B5 and S5–S1, followed by "5-Factor alpha." For portfolio B1–B5, we don't find any reversals (if not further declines) after the portfolio formation quarter, which is consistent with our findings on the baseline abnormal returns.

Next, we check price impact results using dollar-based herding measures, rather than the LSV herding measures that are based on numbers of trades. Our definition of the dollar-based herding measure (DHM) is adapted from Lakonishok et al. (1992) and Wermers (1999), described in detail in Section 3.3. In each quarter, bonds with positive net purchases are sorted into quintiles B1 to B5, with B5 representing the group of bonds with the highest dollar-based buy herding measures. Bonds with negative net purchases are sorted into quintiles S5 to S1, with S5 representing the group of bonds with the highest dollar-based sell herding measures.

Table 14 reports quarterly abnormal returns on portfolios S5–B5, S5–S1, and B1–B5, constructed based on dollar-ratio herding measures. Compared to baseline results in Table 10, we obtain similar results in Table 14 with even greater significance. In particular, quarterly abnormal returns on portfolios S5–B5 and S5–S1 constructed based on dollar-ratio herding measures are strongly positive and in general significant after the portfolio formation quarter, while abnormal returns on portfolios S5–B5 and S5–S1 constructed based on LSV herding measures are only significant for about three quarters after portfolio formation. This improvement on significance holds for all subgroups of corporate bonds. In Fig. 7, we plot cumulative abnormal returns on portfolios constructed based on dollar-ratio herding measures. It shows that when using the dollar-ratio herding measure, not only the significance of results is greater, the magnitude is larger as well. In particular, the magnitude of return reversal gauged by the cumulative abnormal return on portfolio S5–B5 is 4.3% for all bonds and 10.8% for high-yield bonds, larger than the 3.5% and 8.3% obtained from the S5–B5 portfolio constructed based on the LSV herding measure, shown in Fig. 3.

Finally, to address the concern that the price impact of herding is driven by involuntarily divesting downgraded corporate bonds by insurance companies, who are subject to regulation constraints, we exclude all "fallen angels" and repeat the tests. Our results of price impact of herding are qualitatively unchanged after excluding those bonds downgraded to junk status.[43]

To sum, our evidence clearly points to the vulnerabilities associated with correlated trades by institutional investors, robust to a wide variety of checks. In particular, the price-destabilizing effect of sell herding 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.

[43] For results on price impact after excluding the effects of "fallen angels," see our Online Appendix.

Table 14
Robustness on price impact of herding: dollar-based herding measure.
This table reports quarterly abnormal returns (in percent) on portfolios constructed based on bonds' herding measures, for four quarters before the portfolio formation quarter t and six quarters after. Bonds' quarterly abnormal return is defined in Appendix B. Institutional herding is measured in terms of dollars traded, rather than numbers of trades. In particular, $DHM_{i,t} = |Buy\_amount_{i,t} - Sell\_amount_{i,t}|/(Buy\_amount_{i,t} + Sell\_amount_{i,t})$. Dollar-based buy (sell) herding measure is defined as $DBHM_{i,t}(DSHM_{i,t}) = DHM_{i,t}$, if $Buy\_amount_{i,t} > (<) Sell\_amount_{i,t}$. In each quarter, bonds with positive net purchases are sorted into quintiles "B1" to "B5," with "B5" representing the group of bonds with the highest buy herding measures. Bonds with negative net purchases are sorted into quintiles "S5" to "S1," with "S5" representing the group of bonds with the highest sell herding measures. Portfolio S5–B5 is long the equal-weighted portfolio containing bonds that institutional investors most strongly sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that institutional investors most strongly buy as a herd (i.e., B5). Portfolios S5–S1 and B1–B5 are similarly defined. This table also reports quarterly 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. Bonds traded by fewer than five investors in a given quarter are excluded. Bonds issued or maturing within one year are also excluded. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Bond type	$t-4$	$t-3$	$t-2$	$t-1$	Portfolio formation quarter t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Panel A: Quarterly abnormal return on portfolio S5–B5 (in percent)											
All	−0.54***	−0.85***	−0.89***	−0.67***	0.35*	1.05***	1.11***	0.89***	0.27*	0.45**	0.46**
High-yield	−1.72***	−2.59***	−2.59***	−2.35***	0.15	2.30***	2.65***	2.18***	0.73**	1.02**	1.47**
Small	−0.87***	−1.21***	−1.03***	−0.78***	0.42	1.74***	1.48***	1.41***	0.25	0.54*	0.74**
Illiquid	−0.78**	−1.26***	−1.27***	−0.86***	−0.06	1.71***	0.87**	0.75**	0.76**	0.48	1.08**
Panel B: Quarterly abnormal return on portfolio S5–S1 (in percent)											
All	−0.34***	−0.64***	−0.63***	−0.38**	0.61***	1.18***	1.09***	0.87***	0.31**	0.59***	0.37*
High-yield	−0.60**	−1.36***	−1.35***	−0.90***	1.12***	2.86***	2.59***	2.20***	0.67**	1.29***	1.04**
Small	−0.47***	−0.95***	−0.73***	−0.41*	0.82***	1.92***	1.51***	1.28***	0.49**	0.48*	0.42
Illiquid	−0.62**	−1.05***	−0.91***	−0.55*	0.13	1.75***	0.94**	0.71**	0.76**	0.71**	1.04**
Panel C: Quarterly abnormal return on portfolio B1–B5 (in percent)											
All	−0.23***	−0.25***	−0.18***	−0.18***	−0.22***	−0.20***	0.04	0.00	−0.12*	−0.24***	0.03
High-yield	−1.19***	−1.43***	−1.08***	−1.27***	−0.89***	−0.74***	0.19	−0.03	−0.10	−0.56**	0.29
Small	−0.63***	−0.44***	−0.09	−0.14	−0.24*	−0.08	0.02	−0.03	−0.22*	−0.39***	0.11
Illiquid	−0.08	−0.12	−0.33**	−0.17	−0.15	−0.19*	−0.07	−0.03	0.06	−0.22*	0.03

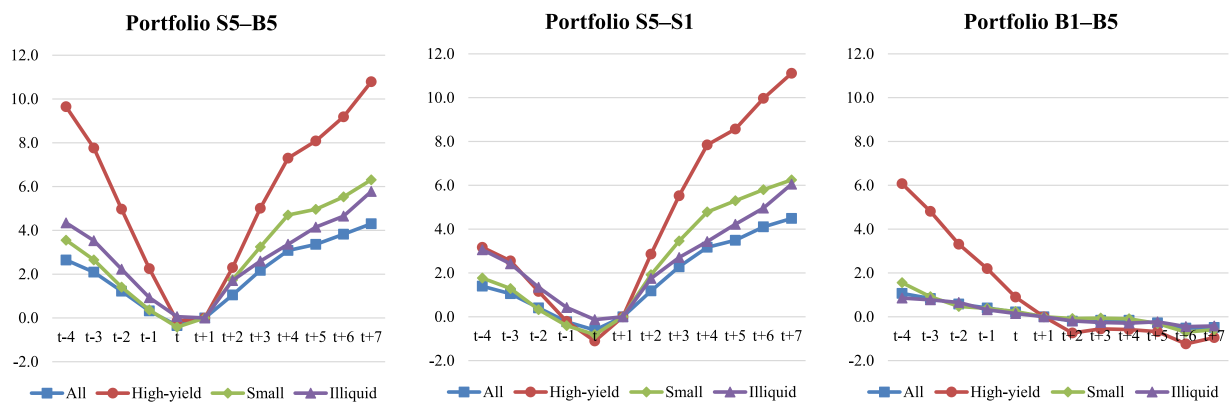

Fig. 7. Robustness on price impact of herding: dollar-based herding measure. This figure illustrates cumulative abnormal returns (in percent) on zero-investment portfolios S5–B5, S5–S1, and B1–B5 before and after portfolio formation quarter t. Bonds' quarterly abnormal return is computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings, industry sectors, and time to maturity. (See Appendix B.) The cumulative abnormal return is indexed to zero at the end of the portfolio formation quarter t. Our definition of the dollar-based herding measure (DHM) follows Lakonishok et al. (1992) and Wermers (1999). In particular, $DHM_{i,t} = |Buy\ Amount_{i,t} - Sell\ Amount_{i,t}|/(Buy\ Amount_{i,t} + Sell\ Amount_{i,t})$. Dollar-based buy (sell) herding measure is defined as $DBHM_{i,t}(DSHM_{i,t}) = DHM_{i,t}$, if $Buy\ Amount_{i,\ t} > (<) Sell\ Amount_{i,\ t}$. In each quarter, bonds with positive net purchases are sorted into quintiles "B1" to "B5," with "B5" representing the group of bonds with the highest dollar-based buy herding measures. Bonds with negative net purchases are sorted into quintiles "S5" to "S1," with "S5" representing the group of bonds with the highest dollar-based 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 sell as a herd (i.e., S5) and short the equal-weighted portfolio containing bonds that institutional investors most strongly buy 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. Bonds traded by fewer than five investors in a given quarter are excluded. Bonds issued or maturing within one year are also excluded.

6. Conclusions

Institutional investors have been playing an increasingly important role in the fixed-income markets, especially the market for corporate bonds, boosted by the significant growth of these investors' market shares in recent years. There have been growing concerns about institutional herding and its potential price impact. In particular, if institutions tend to cluster in selling relatively illiquid securities, these selling herds may cause asset fire sales and accelerated fund outflows, especially during market downturns. This dynamic could become an amplification channel of potential systemic risks.

In this paper, we find that institutional investors do trade in herds in the U.S. corporate 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 on the sell side, driven mostly by institutions following their peers' trades. 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.

Most importantly, 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 clearly points to the financial vulnerabilities associated with institutional herding in the corporate bond markets. We also infer from our price impact analysis that the underlying causes of herding behavior in this market are mixed. The impact of sell herding on bond prices is consistent with theories of imitational herding, which predict loss of information efficiency and excess volatility. In contrast, the effect of buy herding on bond prices is consistent with theories of fundamental-driven herding, which expedites price discovery.

Given the strong destabilizing effect of sell herding, especially during crises, it is critical to develop a deeper understanding of the exact nature of the observed trading behavior. For example, if reputation concerns or compensation structures of asset managers indeed lend themselves toward sell herding, institutional investors may contribute to procyclicality and financial instability even in the absence of leverage. Moreover, future research is needed to explore policy implications of such issues.

Appendix A. Data description

A1. Thomson Reuters eMAXX data

Thomson Reuters licenses eMAXX data that contain survivorship-bias free information on quarter-end holdings of fixed income securities by about 20,000 institutional investors, including mutual funds, pension funds, and insurance companies, which we interchangeably refer to as "funds," "investors," or "institutions" throughout the paper. The type of securities include Treasury/Agency, asset-backed securities (ABS) (including collateralized loan obligations and other ABS), corporate and municipal bonds, and mortgage-backed securities (including both agency and private label), identified by CUSIPs as well as information on institutional investor profiles. Data are at the security level and include North American coverage (based on where the holder is located). Basic fixed income reference data are also included in addition to the holdings data.

Thomson Reuters reports the data sources of eMAXX as follows. Fixed income holdings information for insurance companies is acquired through both National Association Of Insurance Commissioners (NAIC) annual holdings files and the quarterly transaction reports to the state insurance commissioners that are used to interpolate the holdings each quarter. Data on mutual fund holdings are obtained from Lipper, which is owned by Thomson Reuters. The coverage is over 90% of the mutual fund universe. Thomson Reuters also collects data from state and local municipal pension funds and larger private pension funds who voluntarily submit data. For papers that use the eMAXX data, see Bodnaruk and Rossi (2016), Becker and Ivashina (2015), Massa and Žaldokas (2014), Dass and Massa (2014), and Manconi et al. (2012).

A2. Merrill Lynch pricing data

We obtain the Bank of America Merrill Lynch (ML)'s bond pricing data from ML Corporate Bond Index Database. The data contain daily dealer bid prices that start in 1997 for a representative pool of corporate bonds publicly issued in the US domestic market, which constitute the widely used Merrill Lynch US Corporate Investment-Grade and High-Yield indices. Bonds in the two indices must have at least 18 months to final maturity at the time of issuance, at least one year remaining term to final maturity as of the rebalancing date, a fixed coupon schedule, and a minimum amount outstanding of $250 million. Qualifying securities must have an investment-grade rating (based on an average of ratings from Moody's, S&P, and Fitch) to be included in the investment-grade index, and those with below investment-grade rating are included in the high-yield index. Our micro-data include bond CUSIP, daily quoted price, accrued interest, coupon, credit ratings, sector, maturity, and amount outstanding for each bond in the two indices.

Bonds that satisfy the index inclusion criteria automatically get included in the index at index rebalancing dates, which happen at the beginning of each month. In an average month, the two indices combined have around 7000 to 8000 bonds that were issued by U.S.-domiciled companies, totaling roughly $5.2 trillion in terms of outstanding amount. This is about two-thirds of the U.S. corporate bond market, according to estimates from SIFMA. We are able to match 68% of the bond-quarter observations in our herding sample (constructed from the eMAXX data) with the ML pricing data. In terms of amount outstanding, 80%–96%

of corporate bonds in our herding sample can be matched with the ML pricing data, depending on which quarter we look at. For papers that use the ML data, see Acharya et al. (2013), Schaefer and Strebulaev (2008), Gilchrist et al. (2009), and Gilchrist and Zakrajšek (2012).

Appendix B. Independent variables in Model (4.2)

- 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

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

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, industry sector, and time to maturity in that quarter.

The credit rating buckets for financial corporate bonds are (AAA, AA, A, BBB, BB&below). Financial bonds rated as BB and below are combined into one bucket because not many speculative-grade financial bonds are rated. The credit rating buckets for nonfinancial corporate bonds are (AAA&AA, A, BBB, BB, B, C&D). Nonfinancial bonds rated as AAA and AA are combined into one bucket because very few nonfinancial bonds are rated as AAA. Therefore, the rating buckets are as fine as we can possibly achieve. The sector buckets are (financial, industrial, utility). Information on sector categories are provided by Merrill Lynch along with the pricing data. The time to maturity buckets are (1–5 years, 5–10 years, over ten years). This categorization follows the definition of the widely used standard sub-indices produced by Merrill Lynch. In sum, we have five or six rating buckets (depending on whether the bond is financial or not), three sector buckets, and three maturity buckets. After interacting these three ways of sorting, we have 51 benchmark bond portfolios in each quarter. To obtain the abnormal return on an individual bond in a given quarter, we calculate the size-weighted average raw returns on those 51 benchmark portfolios and then subtract the corresponding benchmark raw return from the raw return on that individual bond.
- 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.[44] 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.
  - Amihud (2002) price impact measure, defined as

$$Liq^{Amihud}_{i,d} = \frac{1}{N_{i,d}}\sum_{j=1}^{N_{i,d}} \frac{\left|P^{j}_{i,d}-P^{j-1}_{i,d}\right|/P^{j-1}_{i,d}}{Q^{j}_{i,d}}, \tag{B.2}$$

where $P^j_{i,d}$ and $Q^j_{i,d}$ 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:[45]

$$Liq^{Roll}_{i,d} = 2\sqrt{-cov\left(\Delta P^{j}_{i,d}, \Delta P^{j-1}_{i,d}\right)}. \tag{B.3}$$

  - 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:[46]

$$Liq^{IQR}_{i,d} = \frac{P^{75th}_{i,d}-P^{25th}_{i,d}}{P^{50th}_{i,d}} \times 100. \tag{B.4}$$

We then incorporate all three measures to calculate a comprehensive liquidity measure for each bond in each

[44] 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.

[45] See also Bao et al. (2011) for an application of this measure in examining the illiquidity of corporate bonds and its asset-pricing implications.

[46] 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 et al. (2000) and Hong and Warga (2000).

quarter.[47] 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).

Appendix C. Decompose intertemporal correlations

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

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

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 $q_{i,t-1}$:

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

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 one's own habits, following Sias (2004), we decompose β_t into two components as follows:

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

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 one (zero) 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:

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

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.

[47] 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.

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