Correlated Trading by Life Insurers and Its Impact on Bond Prices

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Abstract:

Our evidence indicates that U.S. life insurers' investment decisions in corporate bonds are correlated across companies within the life insurance industry. On average, sell-side herding is greater in smaller bonds, bonds with lower ratings, and bonds that have been downgraded. Moreover, herding is more pronounced when insurers that are part of a group that has been designated as a SIFI trade the bond. Sell side herding tends to follow negative abnormal returns. Also, bond returns are abnormally low during the quarter when insurers exhibit high sell side herding. However, we do not find that these price effects are subsequently reversed, which is what one would expect if the selling pressure pushed prices away from fundamental values.

Keywords: insurance, bonds, systemic risk

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1. Introduction

Academics, insurance professionals, and regulators continue to debate whether traditional insurance activities of insurers are a source of systemic risk.[1] For example, the Financial Stability Oversight Council (FSOC) in December of 2014 designated MetLife as a systemically important financial institution (SIFI) despite objections from Metlife and other commentators (see e.g., Wallison, 2014). Metlife challenged the ruling, and in March 2016, a judge rescinded the SIFI designation. The Department of Justice on behalf of FSOC has appealed the decision.[2] One argument for why life insurers are a source of systemic risk is that life insurers have investments of over $3 trillion in financial securities and that their trading activity is correlated within the industry, i.e., life insurers herd.[3] As a consequence, life insurers have the potential to disrupt financial markets by causing or exacerbating security price movements away from fundamental values. This is sometimes referred to as the asset liquidation channel (see FSOC (2013) and Getmansky et al. (2016)). Schwarcz and Schwarcz (2014) forcefully make this argument and call for greater regulation.[4]

On the other side of the spectrum from those who argue that life insurers contribute to systemic risk, Vaughan (2012) argues that the life insurance industry provides a stabilizing force in financial markets during times of crisis. This would occur, for example, if during liquidity shocks that induce fire sales from other institutions, insurers maintain their positions and could even potentially step in on the buy side and help stabilize markets. Also, even though U.S. life insurers

[1] Many commentators acknowledge that non-traditional activities, such as trading credit default swaps, could cause insurance groups to be systemically important (see e.g., Cummins and Weiss, 2014 and Harrington, 2009).
[2] MetLife maintains a website containing documents filed related to the debate. See **https://www.metlife.com/sifiupdate/index.html**.
[3] See 2015 Life Insurers Fact Book.
[4] Note that there are other arguments for how insurers could contribute to systemic risk, including concerns about an insolvency of a one insurer reducing confidence in the ability of other insurers to make good on their promises, which in turn could cause policyholder runs and cause insurers to liquidate assets quickly and at fire sale prices. See e.g., Fenn and Cole (1994). Cummins and Weiss (2014) focus on whether reinsurance activities contribute to systemic risk. Also see Acharya et al. (2014), Billio et al. (2012), Chen et al. (2012), Manconi et al. (2012), Weiss and Muhlnickel (2014), and Weiss, et al. (2015).

invest over $2.5 trillion in bonds (about 75 percent of their general account assets) and hold about one-third of all U.S. corporate bonds (McMenamin, et al. (2013)), life insurers are typically buy and hold investors; i.e., their trading activity is much lower than their holdings. These points suggest that life insurers' typical trading activities are unlikely to impact security prices. On the other hand, trading in corporate bonds is relatively thin in general, and so even a relatively small amount of trading can potentially impact prices. Also, recent evidence by Ellul et al. (2011) and Merrill (2014a and 2014b) is consistent with life insurer investment behavior impacting security prices.

Thus, there are arguments on both sides of the debate regarding life insurer investment herding and if it exists, its impact on financial markets. However, there is little research that focuses on the extent to which life insurers herd, and if they do, on whether insurer herding is likely to be disruptive to financial markets. Exceptions include Cai et al. (2012 and 2016), who analyze herding in bond markets by mutual funds, pension funds, and both property-liability and life insurers. Also, Getmanksy, et al. (2016) provide an interesting examination of the interconnectedness of insurance companies' investment decisions using cosine similarity.

Conceptually, there are several reasons why one might expect herding behavior to exist among life insurers. First, life insurers face common accounting and regulatory rules.[5] As a result, one might expect insurers to respond in similar ways (buy or sell the same securities) to changes in these institutional rules and to changes in how a security is treated under these rules. As an example of the latter situation, if a downgrade of a security increases the required risk-based capital that an insurer must hold, then insurers would have greater incentives to sell the security. Second, insurers' financial condition and future prospects are likely to be impacted in similar ways by general economic information (such as changes in interest rates and credit spreads) and to information about the value of specific types of securities. Consequently, insurers might be expected to adjust their portfolios in similar ways in response to economic information. Third, the information cascades theory suggests that company fund managers infer the value of securities from the trades of other

[5] It is also worth noting that often these rules differ from those that apply to other financial institutions, which makes an analysis of life insurers as a group of interest.

fund managers, which in turn leads fund managers to mimic other fund managers' trades (Bikhchandani et al., 1992). Fourth, if the labor market for fund managers assesses ability using relative fund performance, then fund managers will be concerned about poor performance when other funds have good performance. To avoid this outcome, fund managers might mimic each other (Scharfstein and Stein, 1990). Finally, insurers often outsource the management of some of their assets (Kim et al., 2015). As a consequence, the trading activity of insurers using the same outside asset manager could be correlated. Although we examine characteristics of insurers and bonds that are associated with herding, our main purpose is not to distinguish the various explanations for herding. Instead, we identify bond and insurer characteristics that are associated with life insurer herding and examine the impact of life insurer herding on bond prices.

To investigate whether life insurers' corporate bond investment decisions exhibit herding behavior over the 2002-2011 time period, we utilize two herding measures. One is the classic measure introduced by Lakonishok, Shleifer and Vishny (1992), hereafter, the "LSV" measure, which measures the extent to which insurers tend to buy the same securities or sell the same securities within a given time interval using the number of buy trades relative to total trades. The other herding measure, introduced by Oehler and Chao (1990), equals the absolute value of insurers' buy volume minus their sell volume divided by total insurer volume in the bond. Hereafter, we refer to this measure as the volume-based herding measure. As is common in the herding literature, we examine trading behavior over quarterly time intervals.

It is worth highlighting that the LSV herding measure does not incorporate information about the volume of trading in a particular bond. In addition, the LSV measure for a particular bond during a given quarter measures whether insurers' buying or selling of that bond differs from the overall buying or selling in all of the bonds in which insurers transacted during that quarter. In other words, by controlling for aggregate trading of life insurers, the LSV herding measure indicates whether insurers are trading a particular bond differently than insurers are trading bonds in general. In contrast, the volume herding measure for a particular bond simply measures whether insurers as a group are on one side of the market (buy or sell side) in that particular bond. The volume herding measure is therefore analogous to the order imbalance measures used in the literature on the impact of equity market herding on stock prices (e.g., Chordia, et al., 2002 and Dorn et al., 2008).

Our evidence is strongly consistent with life insurer herding. The overall average LSV herding measure for individual corporate bonds is 10.2 percent, which indicates that on average life insurers are about 10.2 percent more likely to be on the same side of the market for individual bonds (either on the buy or sell side) than would be expected if their buy versus sell decisions were independent and consistent with insurer trading of all bonds. We also calculate the buy LSV herding and sell LSV herding measures, as proposed by Wermers (1999). The overall buy and sell LSV herding measures for individual corporate bonds have an average value of 11.1 and 9.4 percent, respectively, indicating that the herding by life insurers is not concentrated on one side of the market. The volume based measures also indicate that on average life insurers herd. For example, when insurer buy volume exceeds insurer sell volume in a bond, it does so on average by a multiple of 3.6, and when insurer sell volume exceeds insurer buy volume in a bond, it does so on average by a multiple of 4.5.

We also examine how the herding measures vary with bond and insurer characteristics. We find that herding by life insurers is greater in smaller bonds and lower rated bonds. This evidence is consistent with herding being more likely when there is greater asymmetric information about the bond's value, which is consistent with the information cascades theory of herding (Bikhchandani et al., 1992). We also find that sell-side herding is greater in bonds that have been recently downgraded, which is consistent with risk-based capital requirements increasing insurers' cost of holding bonds with greater credit risk.

We also investigate the association between herding and "SIFI insurers," insurers that are part of a group that has been designated as a systemically important financial institution (SIFI). The Financial Stability Oversight Council (FSOC) has designated three insurers (AIG, MetLife, and Prudential) as systemically important. Our objective is to provide evidence on whether SIFI insurers are associated with herding behavior. The evidence indicates that, holding other factors constant, herding is on average greater in bonds in which SIFI insurers have a relatively high proportion of the trading volume. Thus, a necessary condition for SIFI insurers to be systemically important through the asset liquidation channel seems to be satisfied – SIFI insurers are associated with investment herding.

Life insurer herding, of course, does not necessarily imply that the herding behavior of life insurers impacts bond prices. There are, however, conditions under which correlated trading is more likely to be stabilizing or destabilizing. We therefore provide evidence on whether these conditions are present when insurers exhibit herding behavior. Correlated trading by life insurers is more likely to be destabilizing if the herding is consistent with momentum trading, i.e., if insurers tend to buy when prices are increasing and sell when prices are decreasing. In this case, insurer trading activity can exacerbate price movements away from fundamental values (see Bank of England, 2014). The opposite pattern would be consistent with insurers' correlated trading providing a stabilizing influence on bond markets (Vaughn, 2012).

We provide two types of evidence on whether insurers' herding is consistent with momentum trading. In panel regression analysis of herding measures, we do not find that herding measures are significantly related to past abnormal returns. Using a different methodology, we compare the abnormal returns on portfolios of bonds that have large buy or sell herding measures to portfolios that do not have large buy or sell herding measures. This approach reveals that sell-side herding tends to occur following poor returns. Additional analysis suggests that this momentum trading is especially strong during the financial crisis.

We also examine abnormal returns on the portfolios in the quarter during and the quarter subsequent to the herding behavior in an effort to examine whether there is evidence of herding impacting bond prices. The results provide some evidence that abnormal returns of portfolios with high sell herding are significantly lower during the herding period than the abnormal returns of portfolios of bonds with low sell herding, especially during the financial crisis and when insurers that are part of a group that has been designated as a SIFI trade the bonds. However, we do not find that the returns rebound in the subsequent quarter, which is what one would expect if the insurer sell herding was temporarily distorting prices. Thus, the evidence is more consistent with insurer sell herding helping to impound information into prices.

The papers most related to this study are by Cai et al. (2012 and 2016). As stated earlier, Cai et al.'s papers examine mutual funds, pension funds, and insurance companies (both property-liability and life companies); whereas, we provide a more focused investigation of herding by life insurers and incorporate insurer characteristics in the analysis. One of the results of the two papers differ: We do not find price reversals following herding; whereas Cai et al. (2016) do find price reversals on average. As discussed later in the paper, we investigate a variety of potential explanations for the different findings.

The paper proceeds as follows. In the next section, we briefly review the literature on herding. The methodology and data are presented in sections 3 and 4. We present descriptive results on how herding varies with bond characteristics, insurer characteristics, and time in Section 5. Panel regression analysis of herding measures are presented in Section 6, followed by the analysis of portfolio returns in Section 7. We end with a summary of the evidence and a discussion of the implications for issues related to the systemic risk of life insurers.

2. Background on Herding

2.1 Determinants of Herding

One explanation for herding among a group of firms in the same industry is that each institution is affected in similar ways by economic information and therefore they each respond to economic information in the same manner (Froot et al., 1992). Correspondingly, insurers that are similar in terms of their products, size, capitalization, and profitability are likely to be impacted similarly by economic information. Consequently, we examine the extent to which herding is related to these insurer characteristics.[6]

[6] Understanding the types of insurers that herd is relevant to identifying insurers that contribute to and/or are exposed to systemic risk. Evidence from Weiss and Muhlnickel (2013) indicates that an insurer's contribution to systemic risk is largely explained by insurer size; whereas, an insurer's exposure to systemic risk is explained by size, the proportion of net revenue earned from investment activities, and proportion of non-policyholder liabilities to total liabilities.

According to the information cascade theory, some institutions infer information from the trades of other institutions and therefore mimic the trading of other institutions (Bikhchandani et al., 1992). Assuming information about smaller bonds (those with a relatively small amount outstanding) and less liquid bonds is more costly to obtain, investors would be more likely to infer information from other institutional investors about these bonds (see Wermers, 1999 and Sias, 2004). According to this explanation, herding would be greater in smaller bonds and less liquid bonds.[7]

There is a growing literature providing evidence that accounting and risk-based capital rules induce insurers to trade in similar ways. For example, Ambrose, et al. (2008, 2012), Ellul et al. (2011), Ellul et al. (2014), and Merrill, et al. (2014b) examine how risk-based capital and accounting rules influence insurers' incentives to sell securities that have been downgraded. Merrill, et al. (2014a) and Becker and Ivashina (2013) examine insurers' incentives to reach for yield within risk-based capital categories. Becker and Opp (2014) and Hanley and Nikolova (2014) respectively examine how insurers' investment decisions changed after the NAIC lowered the risk-based capital requirements for non-agency residential mortgage backed securities (RMBS) in 2009 and for non-agency commercial mortgage backed securities (CMBS) in 2010. Consistent with this literature, we examine whether a bond's rating and the level of insurers' risk-based capital is associated with herding behavior.

Kim et a. (2015) report that outsourcing of investment management services by insurers has increased over the past decade and that over 65 percent of the insurers in the highest quartile of assets have employed at least one investment advisor. If a group of insurers employ the same investment advisor, then the investment advice received across these insurers will likely be correlated, which in turn will likely lead to correlation in investment decisions.

[7] Another explanation for institutional herding arises from managerial agency problems. Scharfstein and Stein (1990) show that if managers' performance across firms is influenced by common factors and that managers care about their reputations for being a good manager, then the labor market will assess a given manager's performance conditional on the performance of other managers. This, in turn, induces a fund manager to mimic other fund managers so that he/she does not "standout" from the group if performance is poor. Dasgupta et al. (2011a) build on this idea in their model of the price impact of herding. Cross-sectional predictions from this framework relate to managerial characteristics, such as manager compensation, age, and experience. Unfortunately, we do not have this type of information.

2.2 Empirical Evidence on Institutional Herding

The majority of the literature on institutional herding examines equity markets.[8] Lakonishok, et al. (1992) introduced the herding measures that we use and that most of the herding literature uses. We refer to these measures as LSV herding measures. They find some evidence that pension funds herd over quarterly periods, although the herding is not strong. Wermers (1999) finds essentially the same results using data on mutual funds. Instead of looking for herding within a quarter, Sias (2004) examines whether herding occurs across quarters. Consistent with institutional herding, Sias (2004) finds that institutional buying in one quarter is correlated with institutional buying in the prior quarter, i.e., herding is persistent from one period to the next. Dasgupta et al. (2011b) also document the persistence of herding behavior.

A number of papers have examined the relationship between herding and the returns earned during the period prior to the herding period, the herding period, and the period subsequent to the herding period. Although there is some variation across the studies, Grinblatt et al. (1995), Wermers (1999), and Nofsinger and Sias (1999) find that positive (negative) stock returns are associated with institutional buy (sell) herding in the period prior, during, and subsequent to when the herding takes place, consistent with momentum trading. Sias (2004) finds that herding is not positively associated with prior period returns once he controls for prior period herding. Dasgupta et al. (2011) also show that persistent herding is negatively correlated with long horizon returns. Gutierrez and Kelly (2009) document similar results.

There are fewer studies that examine herding in bond markets.[9] Oehler and Chao (2000) examine herding by 57 German mutual funds in bonds grouped by similar characteristics and find low LSV herding measures, on average. They also introduce a herding measure based on volume

[8] In addition to institutional herding, there are also studies examining herding by individual investors. See for example, Dorn et al. (2008), who examine retail clients of a large German discount broker, Barber, et al. (2009a, 2009b), who examine clients of two U.S. discount brokers, and Feng and Seasholes (2004), who examine Chinese investors.
[9] The Global Financial Stability Report (2015) reports that herding by both bond and equity mutual funds increased in 2014 relative to 2009.

and find greater herding using the volume based measure than the LSV measure. We adopt their volume based measure.

The papers most similar to this paper are by Cai et al. (2012 and 2016). Cai et al. (2012 and 2016) use changes in quarterly holdings to calculate LSV herding measures; whereas, we use transaction data to calculate both the LSV herding measures and the volume based herding measures introduced by Oehler and Chao.[10] Cai et al. (2012) focus on how herding is influenced by the Financial Industry Regulatory Authority's (FINRA) requirement that bond market trading information be made public. Cai et al. (2016) focus on the extent to which herding is persistent and whether such persistency is due to institutions following themselves or other institutions. In addition, Cai et al. (2016) examine, as we do, abnormal bond price changes around herding. As discussed more below, we find different results than Cai et al. (2016) with regard to the abnormal returns in the post-herding period.

3. Two Herding Measures

3.1 LSV Measures

We begin by describing the herding measure for a group of investors that was originally proposed by Lakonishok, et al. (1992), which we refer to as the LSV measures. In the following description, the investor group could be the entire group of insurers in our sample or a particular subset of insurers selected based on specific characteristics. Let

$\#B_{i,t}$ = the number of insurers from the investor group that were net buyers of bond i during time period t.

$\#S_{i,t}$ = the number of insurers from the investor group that were net sellers of bond i during time period t.

Of all of the insurers from the investor group that transacted in bond i, the proportion that were net buyers is the insurers' buy ratio for security i during period t:

[10] Provided Cai et al. (2016) use the face value of holdings changes, as opposed to the market value of holdings, the difference between transactions within a quarter (which we use) and changes in holdings over a quarter (which they use) should be minimal.

(1) $p_{i,t} = \#B_{i,t} / (\#B_{i,t} + \#S_{i,t})$.

The idea is to test whether the insurers' buy ratio for security i is different than what would be expected given the purchasing and selling activity of the investor group across a broader set of securities. Thus, $p_{i,t}$ is compared to the overall buy ratio during period t, denoted p_t, for a class of securities to which bond i belongs. For example, if security i is a corporate bond with an investment grade rating, then p_{it} could be compared to the overall buy ratio of all investment grade rated bonds. The overall buy ratio is defined as follows:

(2) $$p_t = \frac{\sum_i \#B_{i,t}}{\sum_i \#B_{i,t} + \sum_i \#S_{i,t}} \quad .$$

The absolute difference, $| p_{i,t} – p_t |$, indicates whether the proportion of net buyers of security i differs from the proportion of net buyers in the class of securities.

If insurers' buy versus sell decisions were independent and modeled as a binomial random variable with probability p_t, then the expected value of the absolute difference, $| p_{i,t} – p_t |$, would be positive. Consequently, an adjustment factor is subtracted from the absolute difference to create the herding measure for security i during period t:

(3) $LSV\_HM_{i,t} = | p_{i,t} – p_t | - AF_{i,t}$,

where

(4) $$AF_{i,t} = \sum_{j=0}^{N_{i,t}} \left| \frac{j}{N_{i,t}} - p_t \right| \binom{N_{i,t}}{j} \, p_t^{j} \, (1 - p_t)^{N_{i,t}-j} ,$$

and $N_{i,t}$ is the number of insurers transacting in security i during period t.[11] As $N_{i,t}$ increases, the adjustment factor declines. For example, if $N_{i,t}$ equals three, the adjustment factor is 0.25, but if $N_{i,t}$ equals 25, the adjustment factor is 0.0806.

[11] To illustrate the calculation of the adjustment factor, suppose that there are three insurers transacting in a particular bond and that the probability of a buy transaction (p_t) is ½. Then there are four possible outcomes for the buy ratio: 0, 1/3, 2/3, and 1. The probabilities of these outcomes are 1/8, 3/8, 3/8, and 1/8, respectively. Consequently, the expected value of the absolute difference between the buy ratio and ½ equals

$$\{ \left|\frac{0}{3} - \frac{1}{2}\right| \binom{3}{0} \left(\frac{1}{2}\right)^0 \left(\frac{1}{2}\right)^3 + \left|\frac{1}{3} - \frac{1}{2}\right| \binom{3}{1} \left(\frac{1}{2}\right)^1 \left(\frac{1}{2}\right)^2 + \left|\frac{2}{3} - \frac{1}{2}\right| \binom{3}{2} \left(\frac{1}{2}\right)^2 \left(\frac{1}{2}\right)^1 + \left|\frac{3}{3} - \frac{1}{2}\right| \binom{3}{3} \left(\frac{1}{2}\right)^3 \left(\frac{1}{2}\right)^0 \} =$$

(1/16 + 1/16 + 1/16 +1/16) = ¼, which is the adjustment factor.

Intuitively, a positive value for the herding measure indicates that the group of insurers tend to trade a particular bond in the same direction more than would be expected if their buy versus sell decisions were independent and the probability of a buy equaled the overall buy ratio for insurers during the time period. By averaging the herding measures over time and/or securities, we test whether insurers tend to trade in the same direction, i.e., herd. In addition, we use panel regressions to examine variables that are associated with the herding measure.

Wermers (1999) introduced a buy and a sell herding measure, denoted LSV_BHM and LSV_SHM, by conditioning on whether the security had a higher (lower) buy ratio than the average buy ratio. That is,

$\mathrm{LSV\_BHM_{it}} = \mathrm{LSV\_HM_{it}}$ if $\mathrm{p_{it}} > p_t$ and undefined otherwise,

$\mathrm{LSV\_SHM_{it}} = \mathrm{LSV\_HM_{it}}$ if $\mathrm{p_{it}} < p_t$ and undefined otherwise.

Appendix 1 provides a simple example to illustrate the calculation of the LSV herding measures.

3.2 Incorporating the Information on the Size of Trades

The LSV herding measures take into account the number of trades, but not the size of the trades. Thus, a $50,000 buy transaction is treated the same as a $50 million buy transaction. To incorporate the size of the transaction, we utilize a herding measure used by Oehler and Chao (2000), which takes into account the volume of buy trades and sell trades by insurers. The herding measures based on volume for bond i in quarter t equals the absolute value of the difference between the amount purchased by insurers and the amount sold by insurers as a proportion of the total amount transacted by insurers:

(5) $\mathrm{VOL\_HM_{it}} = |\ \mathrm{Amt\ Purchased_{it}} - \mathrm{Amt\ Sold_{it}}\ |\ /\ [\ \mathrm{Amt\ Purchased_{it}} + \mathrm{Amt\ Sold_{it}}\ ].$

This measure is similar to the order imbalance measures used in a number of equity market studies (see e.g., Chordia et al. (2002)). Analogous to the buy and sell LSV herding measures, we also calculate buy and sell herding measures based on volume and denote them by VOL_BHM and VOL_SHM, respectively. VOL_BHM (VOL_SHM) is the value of the VOL_HM if buy volume of insurers is greater (less) than sell volume by insurers.

In addition to taking into account the amount transacted, the herding measure based on volume differs from the LSV herding measures in that it does not subtract a benchmark measure of insurer buy versus sell volume in the bond market. Stated differently, unlike the LSV measures, the volume based measure does not control for the general movement of insurers in or out of bonds. Instead, the volume based measures incorporate aggregate shifts of insurers in and out of bonds.

4. Data

We examine insurer transactions in individual bonds over quarterly time periods starting in the first quarter of 2003 and ending in the fourth quarter of 2011.[12] The data are from Schedule D, Parts 3, 4, and 5 of insurers' annual statements, which report information on bonds that the insurer purchased during the year (Part 3), sold during the year (Part 4), and bought and sold during the year (Part 5). As reported in Table 1, after deleting non-market secondary transactions and those observations without a reported cusip or a transaction date, there are over 4.5 million bond transactions reported by 1,158 different life insurance companies in 421,039 different bonds issued by 69,466 issuers.[13] For each transaction, the variables reported include cusip, transaction date, type of purchaser (including non-market counterparties such as matured, transferred, called, etc.), cost, par value, and market value.

The transaction data are merged with the Fixed Investment Securities Database (FISD), which provides bond characteristics, including issuance date, maturity date, amount outstanding, coupon rate, and rating history. Following Cai et al. (2012), we restrict the sample to bonds that (a) have remaining maturity greater than two quarters (because bonds with remaining maturity less than two quarters will necessarily leave the insurer's portfolio over the coming quarter), (b) were issued at least three quarters prior (to avoid potential new issue effects), (c) have a fixed coupon,[14] (d) are

[12] The TRACE data are available starting in the third quarter of 2002, but there are relatively few bonds in TRACE for the 3rd quarter of 2002. Since we require return data for the prior quarter, we begin the analysis in the first quarter of 2003.
[13] Non-market transactions are defined by the listed counterparty having one of the following titles: maturity, call, exchange, in-house, pay-down, tax write-off full redemption internal transfer, tender, merged, dividend, basis spinoff, mortgage, or corporate reorganization.
[14] The data do not include information about the formula for variable coupon bonds.

corporate bonds denominated in U.S. dollars (because bond characteristics are missing for most of the other bonds). The number of bonds in the sample drops to 17,316 as a result of this step.

The data are then merged with the Trade Reporting and Compliance Engine (TRACE) data to obtain liquidity, volume, and return measures. Following Bessembinder, et al. (2009) and Dick-Nielsen (2014), we exclude canceled trades, corrected trades, reversal trades, and commission trades. We also follow Rossi (2014) and delete observations that most likely have errors in reported prices.[15] These procedures reduce the number of bonds to 13,689.

The data are also merged with insurer annual statement data to obtain insurer characteristics, such as size and capitalization measures. Insurers with missing or negative value for surplus, total assets, or net premiums written are excluded, which reduces the number of bonds to 12,875. Since most of our analysis will utilize prior quarter bond returns, we drop observations for which we cannot calculate the prior quarter return. The resulting sample has 12,165 bonds traded by 908 life insurers. Recall that the LSV herding measures are calculated using the percentage of buy transactions by insurers in a period (quarter). To ensure that we estimate the buy ratio with some precision, we impose the restriction that each bond in the sample in a given quarter must have transactions from five different insurers. This gives us 176,541 bond transactions in 5,752 bonds by 904 life insurers. The empirical analysis is conducted at the bond-quarter level; there are 23,060 such observations (not tabulated) meeting the screens in Table 1.

In Table 2, we present descriptive statistics for the bond-quarter observations that are used in the subsequent analysis. On average, the bonds transacted are 4.1 years old and had an average maturity when issued of 13.9 years. The average (median) face amount is $860.3 ($551.5) million. Credit Rating takes a value between one and ten, where one indicates the lowest rating (in default) and 10 indicates the highest rating (AAA). To calculate a bond's credit rating, we use the average of

[15] Specifically, we eliminate bond prices with a 50% return reversal (i.e., if the bond price is preceded or followed by a price change of more than 50%) and if the absolute difference between the price and the median price over the prior 10 transactions and subsequent 10 transactions is "large," which is defined using the median of all of the price differences relative to the median of the 20 transactions (i.e., the median of the absolute deviations – MAD). Specifically, we eliminate observations if the absolute difference between the price and the median price over the 20 transactions is greater than $1 + $5*MAD.

three major credit rating agencies ratings and assign the bond to a rating category as described in the following Table.

Avg rating of 4 credit rating agencies	Credit Rating	% of Obs.
AAA	10	0.9%
Above AA	9	3.3%
Above A	8	26.1%
Above BBB	7	36.7%
Above BB	6	15.1%
Above B	5	11.6%
Above CCC	4	3.7%
Above CC	3	0.7%
Above C	2	0.3%
Default	1	0.2%
NR&w	w	0.9%

The average (median) credit rating is 6.9 (7.0) and 67.0 percent of the bonds transacted have an investment grade rating (i.e., above BB).

We calculate a bond's quarterly abnormal return by taking the bond's total return and subtracting the return on a benchmark bond portfolio that consists of bonds with similar ratings and maturity from the bond's total return.[16] The average winsorized abnormal return (at the 1 and 99 percent levels) during the quarter prior to the quarter in which herding is measured is -0.4 percent.

To measure the characteristics of the insurers transacting in the bonds in each quarter, we calculate the weighted average of each insurer's characteristic (e.g., ROA), where an insurer's weight is the proportion of total insurer volume in the bond during the quarter due to that insurer. The average (median) number of insurers transacting in a given bond in a quarter is 7.8 (7.0). The

[16] Our approach to calculating abnormal returns is similar to Bessimbinder et al. (2009). If T is the start of the quarter, then the previous quarter abnormal return equals $\frac{(P_{i,T-1}+AI_{i,T-1})-(P_{i,T-91}+AI_{i,T-91})+C}{(P_{i,T-91}+AI_{i,T-91})} - \frac{I_{i,T-1}-I_{i,T-91}}{I_{i,T-91}}$, where $P_{i,T-x}$ is the bond price on day T-x (x days before the start of the quarter), $AI_{i,T-x}$ is accrued interest on day T-x, and C is the coupon payment(s) received. $I_{i,T-x}$ is the matching portfolio value x days before the first transaction date by an insurer in the quarter. We construct matching portfolios (benchmark portfolios) using all of the bonds in TRACE that can be matched to FISD and that do not have a rating change during the quarter. We classify bonds using the 10 rating categories (AAA, AA, … C, Default) and maturity categories. For investment grade bonds, the maturity categories are 1 to 3 years, 3 to 7 years, 7 to 10 years, and 10 or more years. For non-investment grade bonds, the categories are 1 to 7 years, 7 to 10 years, and 10 or more years. This yields 34 benchmark portfolios. We then subtract the return on the bond in each quarter from the return on the corresponding benchmark portfolio to find the abnormal return. If a bond's rating category changes during a quarter, then we change the benchmark portfolio accordingly.

average (median) winsorized risk-based capital ratio (RBC) is 8.4 (8.1). The distribution of insurer asset size is skewed with a mean of $43.8 billion and a median of $32.3 billion. The average and median return on assets (ROA) is 0.9. The average proportion of volume from insurers that are part of a group that is currently designated as a systemically important financial institution (SIFI) is 0.2. Using 75 percent of premiums written in one line of business as an indicator of product line focus, the average proportion of volume from insurers that focus in life insurance is 13 percent; the average proportion of volume from insurers that focus on annuity business is 39 percent; and the average proportion of volume from insurers that focus in accident and health insurance is 9 percent.

5. Descriptive Analysis of Herding

Table 3 reports the average herding measures for our sample. The average LSV herding measure (LSV_HM) equals 10.2 percent, which indicates that life insurers' tend to buy the same bond or sell the same bond more so than would be expected if their buy and sell decisions were independent. The LSV buy herding measure for the overall sample is 11.1 percent and the LSV sell herding measure for the overall sample is 9.4 percent. These results indicate that the herding behavior of life insurers is not concentrated on the buy or sell side of the market. Instead, both buy and sell decisions are correlated across life insurers.[17]

Also reported in Panel A of Table 3 are the herding measures based on insurer volume of buy and sell transactions. On average, the overall volume herding measure, VOL_HM, is 60.5 percent, indicating that on average insurers are on one side of the market in bonds. The average buy volume herding measure is 56.5 percent, which indicates that when insurers' buy volume exceeds sell volume, the average buy volume is about 3.6 times the sell volume.[18] The average sell herding measure based on volume is 63.7 percent, which indicates that when insurers' sell volume exceeds

[17] If all of the bonds in the initial sample with five transactions are used to calculate the herding measures (98,906), as opposed to those that went through the various data screens outlined in Table 1, the herding measures are higher: LSV_HM = 14.4 percent, LSV_BHM = 11.1 percent, and LSV_SHM = 17.5 percent. If we require only three transactions each quarter instead of five transactions, then the herding measures are lower.

[18] If buy (sell) volume is denoted by B (S), then the volume-based buy herding measure is (B-S)/(B+S). If this measure equals k, then B = S(1+k)/(1-k). If k=.565, then B=3.6 S.

buy volume, the average sell volume is 4.5 times the buy volume. The correlation coefficient between the overall herding measure based on volume, VOL_HM, and the LSV herding measure, LSV_HM, is 0.54.

To put the herding measures in perspective, Panel B of Table 3 reports selected results from the prior literature on herding for other types of institutional investors, securities, and time periods. Generally, the evidence indicates institutional investors have relatively small herding measures for stock transactions (see e.g., Lakonishok et al., 1992 and Wermers, 1999). However, the evidence on bond transactions by institutional investors by Cai et al. (2016) indicates much higher herding measures, consistent with our results.

To provide descriptive evidence on the herding measures, we present a series of graphs in which the LSV herding measures and the volume-based herding measures are plotted versus selected variables. Figures 1 and 2 report herding measures for subsets of bonds based on bond size and bond ratings, respectively. For these analyses, the expected buy ratio (p_t) is the buy ratio for all of the bonds within the category of bonds being considered, as opposed to the buy ratio for all bonds, as was used in herding measures reported in Table 3. For example, in Figure 1, which reports the average herding measure for bonds in four size (amount outstanding) categories, the expected buy ratio for each size category uses only the bonds within that category.

Figure 1A illustrates that the average LSV herding measures are highest for bonds with the lowest amount outstanding (between zero and $20 million) and that the average LSV herding measures decline as the amount outstanding increases. Figure 1B presents the volume-based herding measures for the different bond size categories. The volume-based herding measures also decrease on average as the amount outstanding increases. These results are consistent with existing studies that institutional herding is significantly greater in small stocks. One explanation is that small bonds have less public information, and therefore life insurers are more likely to make decisions based on other insurers' behavior, consistent with informational cascades (Bikhchandani et al., 1992).

Figure 2 illustrates that the average LSV herding measures are lower for investment grade compared to non-investment grade bonds. The volume-based herding measures also indicate that herding is greater in non-investment grade bonds. Several factors could explain this relationship. First, if non-investment grade bonds have greater information asymmetry, which induce insurers to mimic trades of other insurers, then herding would be greater in non-investment grade bonds (Bikhchandani et al., 1992). Second, because of the higher risk-based capital requirements of non-investment grade bonds, insurers (especially those with lower capital) will have an incentive to sell bonds that are downgraded from investment grade to non-investment grade (see Ambrose et al., 2008 and 2012, and Ellul et al., 2011 and 2012). Third, buy herding could result from financially strong insurers purchasing bonds that have been downgraded and that are experiencing downward price pressure from other institutions that are selling these bonds.

Figure 3 illustrates how the average herding measures vary over time. For this analysis, the expected buy ratio (p_t) for the LSV herding measures is calculated using all of the bonds in the sample, as was done in Table 3. Both the LSV and the volume-based average herding measures increase gradually from 2004 through 2009. After reaching a peak in 2009, the average herding measures decrease in 2010 and 2011. Thus, there is some evidence that herding by insurers increased during the financial crisis.

Figure 4 illustrates the average herding measures based on the average risk-based capital ratios of the insurers transacting in the bonds. For this analysis, the expected buy ratio for the LSV measures is calculated using all of the bonds traded by the insurers in the risk-based capital category.[19] The four risk-based capital categories are the quartiles of the average risk-based capital ratios of the insurers in the sample. Figure 4 indicates that the insurers with the lowest risk-based capital ratios have the highest LSV herding measures. However, the volume-based herding measures exhibit the opposite pattern.

[19] For Figure 4, the data are divided into categories by insurer characteristics. Consistent with the construction of the overall sample, we impose the restriction that there must be five transactions for a given bond in a given quarter by the insurers in the same category. As a consequence, there are far fewer bond-quarter observations and the number of observations across the categories in Figure 4 varies even though the RBC ratios are based on the quartile values.

6. Panel Regressions of Herding Measures

6.1 Explanatory Variables

To examine variables that are related to herding in a multivariate context, we present a panel regression analysis of the bond herding measures. The dependent variable is either the overall herding measure (LSV_HM_{it}), the sell herding measure (LSV_SHM_{it}), or the buy herding measure (LSV_BHM_{it}) for bond i during quarter t or the corresponding volume-based herding measures (VOL_HM_{it}, VOL_SHM_{it}, VOL_BHM_{it}). The list of explanatory variables, which includes bond and insurer characteristics, is given in Table 2 with descriptive statistics; more detailed variable definitions are provided in Appendix 2. We also include bond and quarter fixed effects to control for time-invariant unobservable bond characteristics and time effects that may affect the herding level.

We are particularly interested in the coefficient on PrRet, the bond's abnormal return in the previous quarter. A positive coefficient on PrRet in the buy herding regression would be consistent with greater buy herding following price increases and a negative coefficient on PrRet in the sell herding measure would be consistent with greater sell herding following price decreases. Either of these results would be consistent momentum trading by insurers, which would raise concerns about insurers exacerbating price movements.

Table 2 includes four variables related to a bond's rating (the rating level, which varies from 1 to 10 and three dichotomous variables: investment grade, upgrade, and downgrade. We include in the regression a linear spline of the rating variable with a knot at the investment grade cutoff (rating equal to 6 or BB). This allows the sensitivity of herding measures to vary based on whether the bond is investment grade or not. We also include the upgrade and downgrade dummy variables to examine whether new information about the bond's rating influences herding in the quarter of the rating change.

Regarding insurer characteristics, it is useful to highlight two points. First, the insurer financial characteristics are measured as of the prior year end. Second, the insurer characteristics are a weighted average of the values for the insurers that transacted in the bond during the quarter, where an insurer's weight is the proportion of volume in the bond during the quarter due to that insurer. We examine whether the herding measures are related to average insurer size, return on assets, and risk-based capital ratios of the insurers transacting in the bond. Instead of imposing a linear relationship between the herding measures and the average risk-based capital ratios, we include two dichotomous variables; one variable indicates whether the average risk-based capital is less than seven and the other indicates whether the average risk-based capital ratio is between seven and nine. These cutoff values roughly correspond to the 25th and 75th percentile values for the weighted average risk-based capital ratios. We also control for the number of insurers transacting in the bond during the quarter.

In addition, we include a variable, SIFI, which measures the proportion of insurer transaction volume in the bond during the quarter from insurers that are part of a group that has been designated as a systemically important financial institution (i.e., AIG, MetLife, and Prudential). There are on average 27 insurers in the sample from these three groups. The estimated coefficient on this variable indicates whether SIFIs tend to be involved in herding.

6.2 Regression Results

The results of six panel regressions are reported in Table 4. The dependent variables are either the overall herding measure (HM), the buy herding measure (BHM), or the sell herding measure (SHM) using either the LSV approach or the volume-based approach. Regarding bond characteristics, the multivariate analysis reinforces some of the relationships found in the univariate descriptive analysis. First, overall herding and sell herding is greater in smaller bonds, as the coefficient on AmtOutst is negative and statistically significant in each of the HM and SHM regressions. Second, as the bond's rating increases, the herding measures decline, on average. For the overall and sell herding measures, the coefficients on Rating1 and Rating2 are similar, indicating that herding declines as the rating increases at roughly the same rate for non-investment grade and investment grade bonds. The point estimates for the volume based sell herding measures regression indicates that a one unit increase in Rating decreases VOL_SHM by about five percent on average. For the buy herding measures, the coefficient on Rating1 is not significantly different from zero, but the coefficient on Rating2 is negative and statistically significant. The buy herding results suggest that buy herding declines as investment grade ratings improve.

The coefficients on UpGr and DownGr give the estimated impact on herding of a change in the bond's rating during the quarter. We find a significant positive effect of upgrades on the overall and buy volume herding measures. Downgrades are associated with a significant increase sell herding and a decrease in buy herding. On average, a downgrade is associated with a higher LSV (volume-based) sell herding measure of 2.8 (5.3) percent. These findings are consistent with the literature that indicates that insurers tend to sell downgraded bonds (Ambrose et al. (2008, 2011) and Ellul et al. (2011)). The coefficient on the prior quarter abnormal return (PrRet) generally is not statistically significant in any of the regression equations. Thus, there is no evidence from the regressions that herding is related to past abnormal returns on the bond.

Regarding insurer characteristics, the coefficient on the SIFI indicator variable is positive and statistically significant in five of the six regressions, suggesting that herding is greater when insurers that are part of groups that are designated as a SIFI trade the bond, all else equal. Also, there is some evidence that herding tends to be greater when insurers with relatively low RBC ratios trade the bond, all else equal.

Some of the insurer characteristics have a different relationship with the LSV versus the volume-based herding measures. For example, insurer size is negatively associated with the LSV herding measures, but positively associated with the volume-based herding measures, holding other factors constant. The positive association between insurer size and the volume based herding measure is not surprising given larger insurers will, all else equal, have greater trade volumes. Also, the number of insurers transacting in the bond is positively associated with the LSV measures, but negatively associated with the volume-based measures. A likely explanation for these relationships is that the LSV herding measures tend to be larger when a larger number of smaller insurers transact in the bond and that the volume-based herding measures tend to be large even when a small number of large insurers trade a high volume of bonds. Finally, the herding measures based on volume are positively associated with the annuity focus variable, suggesting annuity providers are associated with buy herding.

6.3 Robustness Checks

To examine the impact of the financial crisis on herding, we estimate the regression models for the financial crisis period (2008-2009) separately from the non-financial crisis period (2002-2007, 2010-2011) and use a Chow test to examine whether the coefficients are significantly different in the two periods. To conserve space, we do not tabulate the results. In general, we cannot reject that the coefficient estimates are the same during the financial crisis versus the non-financial crisis. We do find in each of the regressions, a few variables with significantly different coefficient estimates during the financial crisis, but we do not find a consistent pattern that yields an economic interpretation.

We also investigated whether the impact of downgrades on the herding measures depends on whether the rating change crossed the investment grade threshold or not. We find that the positive relationship between downgrades and sell herding as presented in the regressions in Table 4 is not attributable only to downgrades that cross the investment grade threshold. That is, similar effects are observed for downgrades that cross the investment grade threshold and downgrades that do not.[20]

Finally, we examined whether herding measures are affected by whether we use company level or group level data. For the measures used to this point, if two companies in the same group buy a bond in the same quarter, they are considered as two separate buy transactions. One might argue that if investment decisions are made at the group level then these two transactions should be consolidated and treated as one buy transaction, which would result in lower LSV herding measures. If indeed investment decisions are made at the group level, then herding measures based on the consolidated transactions of insurers in the same group might more accurately reflect the extent to which independent organizations herd.

Table 5 presents the average herding measures when the transactions of insurers in the same group are consolidated. We refer to these as the consolidated herding measures. The average LSV

[20] In addition, we investigated whether herding is greater when a bond rating change is not preceded (since the start of the prior quarter) by a prior rating change in the same direction versus when a bond rating change follows a rating change in the same direction since the start of the previous quarter. We refer to the former rating changes as first mover rating changes. We find that both first mover rating downgrades and non-first mover rating downgrades are positively associated with sell herding. See Bewart et al. (2014) for an analysis of the timing of rating changes.

consolidated herding measures are about half the magnitude of those reported in Table 3. For example, the average overall herding measure reported earlier is 10.2 percent and the one reported in Table 5 is 5.7 percent.[21] The volume-based herding measures are also lower than those reported in Table 3. For example, the sell herding measure reported earlier is 63.7 percent and the one reported in Table 5 is 59.4 percent. We also estimated the regression models using the group herding measures and found that most of the relationships revealed by the regressions in Table 4 also hold if group herding measures are used.[22]

7. Relation between Herding and Bond Abnormal Returns

7.1 Overview

We further examine whether life insurer herding is related to past returns using a methodology similar to that employed by Barber et al. (2009) and Dorn et al. (2008) in their studies of equity market herding. We place bonds into portfolios each quarter based on their herding measures and examine whether abnormal returns during the quarter prior to portfolio formation differ between portfolios with high herding measures versus low herding measures.

This methodology also allows us to examine abnormal bond returns during the quarter in which herding occurs (the portfolio formation quarter) and in the subsequent quarter, which provides additional evidence on the impact of life insurer herding on the bond market. Regarding returns during and subsequent to the herding period, there are at least four possible findings and corresponding interpretations:

1. Positive (negative) abnormal returns during the quarter in which buy (sell) herding occurs followed by zero abnormal returns in the subsequent quarter would be consistent with

[21] The number of bonds used to calculate the average herding measures in Table 5 is substantially lower than the number of bonds used to calculate the average herding measures reported in Table 3. The reason is that we require five transactions from different organizations in a quarter for a bond to be included in the sample and consolidation of transactions reduces the number of bonds meeting this requirement. Thus, part of the difference in the average herding measures could be due to the sample of bonds used. Indeed this is the case. If we restrict the bonds to those used in Table 5 but do not consolidate transactions of insurers in the same group, then average herding measures are roughly midway between those reported in Table 5 and those reported in Table 3.

[22] One exception is that we find that the coefficients on the SIFI variable are statistically significant in only two of the six estimated regression equations.

insurers having better information about the value of bonds and that their herding helps to incorporate that information into the price of the bonds.

2. Positive (negative) abnormal returns during the quarter in which buy (sell) herding occurs followed by negative (positive) abnormal returns in the subsequent quarter would be consistent with insurer herding causing price pressure (pushing bond price away from fundamental values), which is relieved in the subsequent quarter.

3. Zero abnormal returns during the quarter in which buy (sell) herding occurs followed by positive (negative) abnormal returns in the subsequent quarter would be consistent with insurers having better information about the value of bonds, but that their herding does not impact prices; instead, the information is impounded in prices in the subsequent quarter.

4. Zero abnormal returns during the quarter in which buy (sell) herding occurs followed zero abnormal returns in the subsequent quarter would be consistent with insurer herding not having an impact on the market.

7.2 Methodology

We place bonds in portfolios based on their buy and sell herding measures and we conduct separate analyses for the portfolios formed using LSV herding measures and the portfolios formed using the volume-based herding measures. For each quarter, we divide all of the bonds in the sample in two categories: (1) those with a non-missing buy herding measure and (2) those with a non-missing sell herding measure. The bonds in the first category are then divided into quintiles based on the magnitude of their buy-herding measures. Portfolio B1_LSV (B1_VOL) consists of the bonds with the lowest buy herding measures in each quarter using the LSV (volume-based) herding measures. Portfolio B5_LSV and B5_VOL consists of the bonds with the highest buy herding measures. We repeat the same ranking procedure for bonds with non-missing sell-herding measures, creating portfolios S1_LSV (S1_VOL) to S5_LSV (S5_VOL), where portfolio S1_LSV (S1_VOL) consists of the bonds with lowest LSV (volume-based) sell herding measures in each quarter and S5_LSV (S5_VOL) consists of the bonds with the highest LSV (volume-based) sell herding measures each quarter.

Table 6 provides information about the portfolios formed using the LSV measures and Table 7 provides information about the portfolios formed using the volume-based measures. The first three columns of each Table provide descriptive information about the average number of bonds in each portfolio and the average herding measure over the sample period.[23] The other three columns report the average abnormal returns on each portfolio in (1) the quarter prior to portfolio formation, (2) the quarter in which the portfolio is formed, and (3) the quarter after the portfolio is formed. Our focus is on the difference in the abnormal returns between the portfolios with high buy (sell) herding, i.e., B5 and B4 (S5 and S4) and the portfolio with the lowest buy (sell) herding, i.e., B1 (S1). In other words, we are interested in the differential impact of high buy (sell) herding versus low buy (sell) herding on bond returns. This approach also helps to control for common factors affecting bond returns during a quarter that are not captured by our benchmark portfolios.

Focusing first on Table 6, the average buy herding measure in B5_LSV is 36.2 percent and the average sell herding measure in S5_LSV is 29.8 percent, both of which suggest a substantial degree of herding in the bonds in these portfolios. Portfolios B4_LSV and S4_LSV have average herding measures of 20.9 percent and 20.7 percent, respectively; these numbers also suggest a high degree of herding in the bonds in these portfolios. In contrast, portfolios B1_LSV and S1_LSV have LSV herding measures that are negative, indicating little herding in the bonds in these portfolios. Similarly, Table 7 indicates that B5_VOL and B4_VOL have high buy herding measures based on volume and S5_VOL and S4_VOL have high sell herding measures based on volume; whereas, B1_VOL and S1_VOL have low herding measures.

For each of these 10 portfolios and for each of the 36 quarters, we calculate the equally-weighted abnormal returns for the quarter before, the quarter of, and the quarter after the portfolio formation quarter. The abnormal returns are calculated using a matching portfolio methodology similar to that in Bessembinder, et al. (2009).[24] This is repeated for each bond in the herding

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[23] The average number of bonds in the various portfolios can vary slightly due to the way that ties (bonds with the same value of the herding measure) are treated.

[24] As is well-known, the secondary corporate bond market in general exhibits thin trading, i.e., many bonds do not trade on a daily basis. In addition, not all transactions are reported in TRACE (our source of bond price

portfolio for each quarter and the resulting values are averaged to calculate the average abnormal return for the portfolio for that quarter. These quarterly average abnormal returns are then averaged over the 36 quarters to calculate the overall average abnormal return for each of the 10 portfolios. To account for heteroscedasticity in the abnormal returns, we base statistical significance on standardized abnormal returns using a sign-rank test (Ederington et al. 2014).[25]

7.3 Results

Table 6 reports the average abnormal returns for each of the 10 portfolios and the difference in abnormal returns for the portfolios with high herding and low herding. For the high buy herding portfolios, B5_LSV and B4_LSV, the abnormal returns are not statistically different from the abnormal returns for the low buy herding portfolio (B1_LSV) in any of the time periods, except for subsequent quarter.

The high sell herding portfolios, S5_LSV and S4_LSV, however, have abnormal returns that are statistically different from the abnormal returns for the low sell herding portfolio (S1_LSV) in the quarter prior to portfolio formation. For the quarter prior to portfolio formation, the difference in the abnormal return between S5_LSV and S1_LSV is -1.39 percent, which is large economically and statistically significant at the one percent level. This finding indicates that bonds in which insurers exhibit strong sell herding behavior tend to have lower returns in the prior quarter than bonds in which insurers do not exhibit sell herding, which is consistent with sell herding occurring in bonds that have recently performed poorly.

For the herding period, the difference in abnormal returns between S5_LSV and S1_LSV and also between S4_LSV and S1_LSV are negative, large economically, but not statistically significant. There is no evidence that there is a rebound in prices in the subsequent quarter relative to bonds with no herding. Indeed, the S5_LSV – S1_LSV portfolio continues to have negative abnormal returns in

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information). Consequently, when no transaction is reported in the TRACE data for one of the days of interest to us, we use the nearest prior transaction price in TRACE.

[25] We use the cross-sectional standard deviation to scale the abnormal returns. Ederington et al. (2014) recommend using both cross-sectional and time series measures of standard deviation, but given that we use quarterly data over nine years, we do not have enough time series observations to incorporate a time series standard deviation for the first part of our sample period.

the subsequent quarter (although not statistically different from zero). Thus, the evidence does not suggest price pressure effects that are relieved in the subsequent quarter.

The results when herding is defined using volume are presented in Table 7. Consistent with the previous results, this evidence indicates that buy herding is not associated with abnormal returns in the prior quarter. However, we find positive abnormal returns in the herding quarter, but no subsequent reversal. This is consistent with buy herding helping to incorporate information into prices.

The results using sell herding based on volume indicates negative abnormal returns in the quarter prior to portfolio formation, which again is consistent with sell herding by insurers following poor returns. Our evidence also indicates large negative abnormal returns in the herding quarter, Again, we do not find abnormal performance in the subsequent quarter when herding is defined using volume, which is inconsistent with sell herding pushing prices below fundamental values.

Our results differ from Cai et al. (2016) who find that significant price reversals following sell side herding by mutual funds, pension funds, and insurance companies. In light of Cai et al.'s results, we conducted a number of robustness checks:

(1) We extended our post-herding period to two quarters and also to three quarters, but we still did not find evidence of reversals.

(2) The analysis above uses transaction prices to calculate abnormal returns; whereas, Cai et al. (2015) use Merrill Lynch quoted prices. To explore whether transaction prices versus quoted prices explain the different results, we gathering quoted prices from Bloomberg. We are able to download historical Bloomberg quoted prices only for bonds that were still outstanding as of September 2016. Consequently, this sample is smaller than our main sample and consists of longer maturity bonds than the main sample. The results are summarized in Table 8. Although the statistical significance of the results using quoted prices differ somewhat from our baseline results (presented in Table 6 and 7), the implications are similar, i.e., (a) sell side herding is preceded by negative abnormal returns, (b) during the herding period, there is evidence of positive abnormal returns for buy herding and negative abnormal returns for sell herding, (c) no

evidence of price reversals in the post herding period. Note that this analysis does not completely rule out the possibility that the explanation for the different results is the use of different price data, as our quoted prices are from a different source than Cai et al. (2016).

(3) Our method of calculating abnormal returns differs from Cai et al. (2016). We therefore redo our analysis using raw returns; a summary of the results is presented in Table 9. The raw return results are similar to those using abnormal returns, except that we find large positive returns in the quarter following portfolio formation for the high sell herding portfolios relative to the low sell herding portfolios using both the LSV and the volume based herding measures. In only one instance, however, is the difference between the high and low sell herding portfolios statistically significant at the 10 percent level.[26] Given the statistical evidence is weak and conceptual arguments for using abnormal returns as opposed to raw returns are strong, we place relatively little weight on these results. Nevertheless, the analysis suggests that a potential explanation for the different results is the different benchmarks used to calculate abnormal returns.

7.4 Impact of the Financial Crisis

One might argue that if insurer herding were to impact prices, it would be most likely to occur during periods when financial markets are in turmoil. Therefore, we redo the bond price analysis for the period before, during, and after the financial crisis. The use of quarterly data inhibits an in-depth analysis of this issue because of the few number of observations during the financial crisis and therefore the week power of any statistical tests. Nevertheless, in Table 10 we report the results of the portfolio analysis for three separate time periods: 2002-2007, 2008-2009, and 2010-2011. Given the relatively few observations in each period, we focus on economic magnitudes in our discussion.

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[26] Another possible explanation for the different results, which is related to our analysis of raw returns, is the method of testing for statistical significance differs between the two studies. As noted earlier, we use the cross-sectional standard deviation to scale the abnormal returns when testing for statistical significance (see Ederington et al. (2014)). Cai et al. (2016) do not report how they calculate statistical significance. If we do not standardize abnormal returns, then the raw returns in the quarter after sell herding reported in Table 9 are statistically significant at the 5 and 10 percent level.

The striking feature is the large negative abnormal return during the financial crisis for the bonds with high sell herding (S5) relative to bonds with low sell herding (S1) during the quarter before herding. The difference in these portfolios is -3.78 percent when the LSV measures of herding are used and -2.58 percent with the volume-based herding measure. Thus, the evidence suggests that sell herding following poor bond performance was especially pronounced during the financial crisis. The abnormal return results during the financial crisis for the quarter after sell-side herding occurs are mixed. For example, using the LSV herding measure, the differences between the abnormal returns for the high sell-side herding portfolios and the low sell-side herding portfolio, S5-S1 and S4-S1, are -0.90 percent and 1.44 percent, respectively. While neither difference is statistically significant, the -0.90 percent abnormal return suggests no price reversal, but the 1.44 percent return suggests a price reversal.

7.5 Abnormal Returns on Bonds in which SIFIs Herded

We now examine whether the impact of herding on bond prices differs when the bonds are more heavily traded by SIFIs. It is worth noting that the Financial Stability Oversight Council (FSOC) has been criticized for designating some institutions as SIFIs without explaining the underlying process or factors that influence this designation (Wallison, 2014). If we find that SIFI insurers are associated with bond price impacts, then the evidence would lend credence to the argument that herding is one of the channels by which these insurers are systemically important.

We start by dividing the bond-quarter observations in two categories called SIFI and Non-SIFI, where the former includes all of the bonds for which insurers that are part of a group that is classified as a SIFI accounted for 15 percent or more of the total insurer trading volume in the bond during the quarter. The Non-SIFI Traded group consists of all of the other bonds. We also used a 25 percent cutoff to define the SIFI Traded group and found similar results.

We report results using the volume-based herding measure, but the results are similar if we use the LSV herding measure. Within each group, the bonds with non-missing buy herding measures are evenly divided into three portfolios. Portfolio BP1 consists of the bonds with the highest one-third buy herding measures and portfolio BP3 consists of the bonds with the lowest one-third buy herding measures. For both the SIFI and Non-SIFI groups, we examine the difference in the abnormal returns between BP1 and BP3. Similarly, the bonds with non-missing sell herding measures are evenly divided into three portfolios, with SP1 (SP3) being the portfolio with the highest (lowest) one-third sell herding measures. For both the SIFI and Non-SIFI groups, we examine the difference between the abnormal returns of SP1 and SP3.[27]

Table 11 reports the abnormal bond returns for high buy herding versus low buy herding (BP1-BP3) and for high sell herding versus low sell herding (SP1-SP3) for bonds with heavy trading by SIFIs versus bonds without heavy trading by SIFIs. The main result is that during the portfolio formation quarter, the high sell herding portfolio performs worse than the low sell herding portfolio when the bonds are heavily traded by SIFIs, as the difference in abnormal returns is -1.21 percent, which is statistically significant at the one percent level. In contrast, when the bonds are not heavily traded by SIFIs, the difference in abnormal returns is -0.35 percent and not significantly different from zero.

Thus, our evidence indicates that the prices of bonds in which herding takes place fall on average during the herding period when SIFI insurers are heavily involved in herding, but prices do not fall on average when other insurers herd. Stated differently, when herding impacts prices, SIFIs tend to be involved. If one of the objectives in identifying certain insurers as SIFIs was to identify insurers that can impact security prices, then it appears that the objective was achieved. Of course, impacting prices can be a good outcome if the SIFIs are impounding information into the bond's price. Our evidence suggests that this is the case, as the alternative interpretation that SIFIs are pushing the bond price below fundamental values is inconsistent with our findings of no rebound in the price in the subsequent quarter.

[27] We use six as opposed to the ten portfolios as we did in the analysis reported above to ensure a sufficient number of bonds in each portfolio given we have already split the sample in two groups based whether the bonds were traded heavily by SIFIs.

8. Summary and Implications for the Systemic Risk of Life Insurers

Using two different measures of investment herding (correlated trading) among institutions, we find that U.S. life insurers' investment decisions in corporate bonds are consistent with herding behavior. That is, on average life insurers tend to be on the same side of the market (either buying or selling) in individual corporate bonds than would be expected if their investment decisions were independent of each other. Sell side herding among insurers is more pronounced in smaller bonds, lower rated bonds, and bonds that have been downgraded. Herding is also more pronounced when insurers that are part of groups that have been designated as systemically important (SIFIs) trade the bonds.

Correlated trading among life insurers is one of the channels that has been put forth for why life insurers could contribute to systemic risk (see Schwarcz and Schwarcz, 2014). The evidence that insurers do herd therefore lends credence to the argument that life insurers' investment activities could be a source of systemic risk. However, correlated trading does not imply that life insurers' investment decisions have a negative impact on market prices. Thus, we also examine the relationship between herding behavior and bond abnormal returns. We do find some evidence that sell herding follows poor bond performance, which would suggest that sell side herding could potentially exacerbate price declines. However, based on abnormal returns during the quarter in which herding takes place and in the subsequent quarter, we find little evidence that insurer herding caused prices to move away from fundamental values during our sample period.

What are the implications of the results for the issue of whether insurers are systemically important, i.e., whether life insurers could potentially initiate or exacerbate a financial crisis? Before addressing this issue, it is important to highlight that our analysis and discussion only addresses one possible channel by which insurers could be systemically important – the investment herding channel. We believe the evidence in this paper is mixed as to whether insurers' investment behavior has the potential to disrupt financial markets. On the affirmative side, we do find evidence of investment herding and evidence that sell side herding by insurers follows bond price declines. On the other hand, we find little evidence that this herding pushes prices away from fundamental values.

Of course, not finding evidence in the recent past that insurer herding pushes prices away from fundamental values does not necessarily imply that it cannot do so in the future.

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Table 1
Sample Selection Process

Life Insurer bond transactions are from Schedule D, Parts 3, 4, and 5 of life insurer annual statements.

Step	Total Sample	Bond Transactions	Bond Issues	Bond Issuers	Insurance Companies
1	Life Insurer bond transactions from 2003-2011 after deleting obs. with no cusip, no transaction date, and non-secondary market trades	4,588,248	421,039	69,466	1,158
2	Merged with FISD & require - maturity >2 quarters - age > 3 quarters - fixed coupon - corporate bond - credit rating	482,567	17,316	5,024	965
3	Merged with TRACE	423,500	13,689	3,816	964
4	Merged with Insurer data	382,084	12,875	3,675	908
5	Merged with previous returns	347,632	12,165	3,556	904
6	Require 5 transactions per quarter	176,541	5,752	2,088	904

Table 2

Characteristics of Bonds and Insurers in the Sample

Maturity is the number of years until the bond matures. Bond Age is the number of years that the bond has existed. Face amount is the face amount of the bond ($millions). Credit Rating is the average of the S&P, Moody's, and Fitch ratings and takes a value between 1 and 10 with 10 being AAA, 9 above AA, etc. Investment grade is equal to one if the bond is investment grade (rating above BB) and zero otherwise. Amihud Liquidity is the measure of liquidity in Amihud (2002) winsorized at the 1 and 99 percentile values. Prior quarter return is the abnormal return in the previous quarter winsorized at the 1 and 99 percentile values. The insurer characteristics are for the prior year and are volume-weighted averages of the variable for the insurers transacting in the bond in the quarter. #InsTrans = the number of insurers transacting in the bond during the quarter, PctVol_SIFI is the proportion of insurer volume in the bond from companies that are part of a group that has been designated as a SIFI. RBC is the risk-based capital ratio, winsorized at the 1 and 99 percentile values. Assets is total assets ($billions). LogAssets is the natural logarithm of total assets. I(Life Bus >75%) equals one if the percentage of premiums written from life insurance exceeds 75 percent and zero otherwise. I(Ann Bus > 75%) equals one if the percentage of premiums written from annuities exceeds 75 percent and zero otherwise. I(A&H Bus > 75%) equals one if the percentage of premiums written from accident and health insurance exceeds 75 percent and zero otherwise. Values are based on 20,760 bond-quarters.

Bond Characteristics	Var Name	Mean	Median	Min	Max	Stdev
Maturity when issued (yrs.)		13.9	10.0	2.0	100.0	9.1
Bond Age (yrs)	Age	4.1	3.3	1.0	24.3	2.7
Face Amount ($mill)		860.3	551.5	0.1	7,362.8	830.7
Ln(Face Amount) ($mill)	AmtOutst	13.3	13.2	3.9	15.8	0.8
Credit Rating	Rating	6.9	7.0	1.0	10.0	1.2
Investment Grade (%)	InvGr	72.6	100.0	0.0	100.0	44.6
Upgraded (in %)	UpGr	2.7	0.0	0.0	100.0	16.3
Downgraded (in %)	DownGr	7.2	0.0	0.0	100.0	25.9
Prior qtr Return (in %)	PrRet	-0.4	-0.2	-24.7	21.3	5.5
Amihud Liq. measure	Liquidity	0.7	0.4	0	5.0	0.8
Insurer Characteristics						
# of Insurers transacting	#InsTrans	7.8	7.0	5	72	3.8
Avg Risk-Based Capital Ratio	Avg RBC	8.4	8.1	5.2	20.0	2.2
Avg Return on Assets (in %)	Avg ROA	0.9	0.9	-33.3	28.0	2.1
Avg value of Assets ($billions)		43.8	32.3	0.1	237.0	37.5
Avg Log(Assets)	AvgLogAssets	23.5	23.6	17.7	26.2	1.0
% of volume by SIFIs	PctVol_SIFI	21.3	2.9	0.0	1.0	29.2
Avg I(Life Bus > 75%)	Avg Life_Foc	0.13	0.04	0.00	1.00	0.19
Avg I(Ann Bus > 75%)	Avg Ann_Foc	0.39	0.37	0.00	1.00	0.29
Avg I(A&H Bus > 75%)	Avg AH_Foc	0.09	0.01	0.00	1.00	0.15

Table 3

Herding Measures

The overall herding measure, LSV_HM, is based on the absolute value of the difference between the proportion of insurers buying a particular bond relative to the proportion of insurers buying any bond during the quarter. The buy (sell)) herding measure, LSV_BHM (LSV_SHM), is the value of LSV_HM if the difference between the proportion of insurers buying the bond is greater (less) than the proportion of insurers buying any bond during a given quarter, and missing otherwise. The overall volume based herding measure, VOL_HM, is equal to the absolute value of the difference between insurers' buy volume and sell volume, divided by insurers' total volume. The buy (sell) herding measures based on volume, VOL_BHM (VOL_SHM) equal the value of VOL_HM if the buy volume of insurers is greater (less) than the sell volume of insurers in the bond during the quarter, and missing otherwise.

Panel A: Herding Measures for Sample of Insurers Transacting in Corporate Bonds from 2002 - 2011

Variable	N	Mean	StdDev
LSV_HM	20,760	10.2%	15.8%
LSV_BHM	10,204	11.1%	16.4%
LSV_SHM	10,556	9.4%	15.3%
VOL_HM	20,760	60.5%	33.6%
VOL_BHM	9,029	56.5%	33.3%
VOL_SHM	11,723	63.7%	33.5%

Panel B: Representative Results from the Literature on Institutional LSV Herding Measures

Reference	Institutions	Securities	Time Period	Mean HM	Mean BHM	Mean SHM
Lakonishok et al. (1992)	Pension funds	Stocks	'85-'89	2.7%		
	Pension funds	Small stocks	'85-'89	6.1%		
	Pension funds	Large stocks	'85-'89	1.6%		
Wermers (1999)	Mutual funds	Stocks	'75-'95	3.4%	2.9%	3.7%
	Mutual funds	Small stocks	'75-'95	6.2%	3.7%	8.1%
	Mutual funds	Large stocks	'75-'95	2.7%	2.5%	2.8%
Cai, et al. (2016)	Insurers	Corp bonds	'98-'14	13.2%	13.3%	12.5%
	Mutual funds	Corp bonds	'98-'14	9.6%	8.4%	10.8%
	Pension funds	Corp bonds	'98-'14	8.6%	9.0%	7.9%

Table 4
Panel Regressions for Herding Measures

Dependent variable is one of the six herding measures for bond i during quarter t described in Table 3. The explanatory variables include the following characteristics of bond i during quarter t: Age = age in years. AmtOutst = logarithm of average amount outstanding. Rating = average rating score (1=default, 10==AAA); Rating1 is the first segment of a linear spline of Rating and Rating2 is the second segment. The knot for the spline is at 6, the threshold for an investment grade rating. Upgr = 1 if bond is upgraded at least once during quarter, and 0 otherwise; Downgr = 1 if the bond is downgraded at least once during quarter, and 0 otherwise; Liquidity = average Amihud liquidity measure. PrRet = the previous quarter's winsorized abnormal return for bond i.

#InsTrans = the natural logarithm of the number of insurers transacting in the bond during the quarter, PctVol_SIFI = the proportion of insurer volume in the bond from companies that are part of a group that has been designated as a SIFI. The other insurer characteristics are weighted averages of the insurer characteristics, where the weight is the percentage of volume from the insurer. Avg RBC = winsorized average risk-based capital ratio; AvgRBC<7 (7≤Avg RBC<9) is a dichotomous variables that equals zero unless the Avg RBC ratio is less than 7 (between 7 and 9), in which case the variable equals one; Avg ROA = average return on assets; and Avg LogAssets = average logarithm of inflation adjusted general account assets; Avg Life_Foc, Avg Ann_Foc, and Avg AH_Foc, give the average value of the dichotomous variable indicating whether an insurer has 75% of its premium revenue from life, annuities, or accident & health insurance, respectively.

Coefficients are reported with robust standard errors in parentheses. Bond and quarter fixed effects are included in the regressions. ***, **, * indicate significance at the 0.01, 0.05, 0.10 level, respectively.

	LSV_HM	VOL_HM	LSV_BHM	VOL_BHM	LSV_SHM	VOL_SHM
Age	-0.033	0.072	-0.062	-0.126	0.013	0.269***
	(0.030)	(0.064)	(0.056)	(0.127)	(0.046)	(0.095)
AmtOutst	-0.045***	-0.097***	0.017	-0.017	-0.044***	-0.086***
	(0.008)	(0.016)	(0.030)	(0.083)	(0.010)	(0.016)
Liquidity	0.001	-0.001	-0.004	-0.014	0.006	0.006
	(0.002)	(0.005)	(0.005)	(0.010)	(0.004)	(0.007)
Rating1	-0.033***	-0.059***	-0.010	0.018	-0.037***	-0.052***
	(0.005)	(0.010)	(0.022)	(0.043)	(0.006)	(0.011)
Rating2	-0.032***	-0.065***	-0.023**	-0.064**	-0.023***	-0.050***
	(0.005)	(0.011)	(0.012)	(0.026)	(0.008)	(0.016)
UpGr	0.006	0.045**	0.015	0.070**	-0.010	0.033
	(0.009)	(0.018)	(0.016)	(0.034)	(0.013)	(0.027)
DownGr	0.006	0.045***	-0.038**	-0.052	0.028***	0.053***
	(0.006)	(0.012)	(0.016)	(0.038)	(0.008)	(0.015)
PrRet	-0.035	-0.066	-0.075	-0.080	-0.021	-0.084
	(0.028)	(0.054)	(0.065)	(0.141)	(0.038)	(0.073)
PctVol_SIFI	0.018***	0.048***	0.038***	0.049*	0.013	0.038**
	(0.006)	(0.013)	(0.011)	(0.025)	(0.010)	(0.019)
# InsTrans	0.044***	-0.109***	0.038***	-0.143***	0.052***	-0.093***
	(0.004)	(0.009)	(0.008)	(0.017)	(0.007)	(0.013)
Avg RBC<7	0.015***	0.025***	0.016*	0.022	0.009	0.025*
	(0.005)	(0.010)	(0.009)	(0.019)	(0.007)	(0.015)
7≤Avg RBC<9	0.007*	0.008	0.004	0.005	0.006	0.010
	(0.004)	(0.008)	(0.007)	(0.016)	(0.006)	(0.012)
Avg ROA	-0.092	-0.178	-0.200	-0.596	0.068	-0.017
	(0.091)	(0.184)	(0.167)	(0.363)	(0.142)	(0.265)
Avg LogAssets	-0.006***	0.012***	-0.012***	-0.002	-0.001	0.022***
	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.006)
Avg Life_Foc	-0.000	0.026	0.004	0.055	0.002	0.029
	(0.009)	(0.019)	(0.016)	(0.036)	(0.014)	(0.027)
Avg Ann_Foc	0.001	0.039***	-0.007	0.053**	0.008	0.034*
	(0.006)	(0.013)	(0.011)	(0.024)	(0.010)	(0.018)
Avg AH_foc	0.013	0.013	0.019	0.007	0.012	0.010
	(0.012)	(0.026)	(0.021)	(0.051)	(0.019)	(0.037)
Constant	0.957***	2.097***	0.196	1.128	0.730***	1.478***
	(0.124)	(0.240)	(0.432)	(1.166)	(0.154)	(0.267)
R^2	0.38	0.38	0.50	0.52	0.55	0.52
N	20,760	20,760	10,204	9,029	10,556	11,723

Table 5

Impact of Consolidating Transactions of Insurers in the Same Group on Average Herding Measures

Transactions of insurers in the same group during the same quarter are consolidated to calculate the various herding measures. The overall herding measure, LSV_HM, is based on the absolute value of the difference between the proportion of insurers buying a particular bond relative to the proportion of insurers buying any bond during the quarter. The buy (sell)) herding measure, LSV_BHM (LSV_SHM), is the value of LSV_HM if the difference between the proportion of insurers buying the bond is greater (less) than the proportion of insurers buying any bond during a given quarter, and missing otherwise. The overall volume based herding measure, VOL_HM, is equal to the absolute value of the difference between insurers' buy volume and sell volume, divided by insurers' total volume. The buy (sell) herding measures based on volume, VOL_BHM (VOL_SHM) is the value of VOL_HM if the buy volume of insurers is greater (less) than the sell volume of insurers in the bond during the quarter, and missing otherwise.

Variable	N	Mean	StdDev
LSV_HM	12,042	5.7%	14.6%
LSV_BHM	6,039	6.0%	14.6%
LSV_SHM	6,003	5.5%	14.5%
VOL_HM	12,042	56.4%	32.3%
VOL_BHM	5,2673	52.6%	31.4%
VOL_SHM	6,775	59.4%	32.7%

Table 6
Abnormal Returns Based on Transaction Prices
for Portfolios formed Based on LSV Herding Measures

Average abnormal returns for 10 portfolios formed in each of 36 quarters from the 1st quarter of 2003 through 2011. B1_LSV (B5_LSV) consists of bonds with the lowest (highest) LSV buy herding measures during each quarter and S1_LSV (S5_LSV) consists of bonds with lowest (highest) LSV sell herding measures during each quarter. Abnormal returns are calculated using 34 benchmark portfolios as described in the text and winsorized at the 1% and 99% values. Statistical significance is based on a sign rank test of standardized abnormal returns.

			Average Abnormal Returns		
Buy Herding Portfs	Avg # of bonds	Average BHM	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B1_LSV	55	-9.7%	0.01%	0.03%	-0.40% **
B2_LSV	57	-0.1%	-0.12%	-0.08%	-0.25% *
B3_LSV	57	10.0%	-0.19% *	-0.08%	-0.26%
B4_LSV	56	20.9%	-0.28%	0.13%	-0.10%
B5_LSV	55	36.2%	-0.18%	0.17%	-0.06%
B5_LSV – B1_LSV			-0.20%	0.14%	0.34%
B4_LSV – B1_LSV			-0.29%	0.10%	0.30% **

			Average Abnormal Returns		
Sell Herding Portfs	Avg # of bonds	Average SHM	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S1_LSV	57	-11.1%	-0.03%	-0.34% *	-0.28% *
S2_LSV	59	-1.1%	-0.32% ***	-0.46% **	-0.31% **
S3_LSV	57	8.9%	-0.68% ***	-0.66% **	-0.53% ***
S4_LSV	56	20.7%	-0.61% ***	-1.12% ***	-0.28%
S5_LSV	52	29.8%	-1.41% ***	-1.14% ***	-0.71% **
S5_LSV - S1_LSV			-1.39% ***	-0.80%	-0.43%
S4_LSV - S1_LSV			-0.59% *	-0.78%	0.00%

Table 7

Abnormal Returns Based on Transaction Prices

for Portfolios formed using Herding Measure Based on Insurer Volume

Average abnormal returns for 10 portfolios formed in each of 36 quarters from 2003 through 2011. B1_VOL (B5_VOL) consists of bonds with the lowest (highest) volume based buy herding measures during each quarter and S1_VOL (S5_VOL) consists of bonds with lowest (highest) volume based sell herding measures during each quarter. Abnormal returns are calculated using 34 benchmark portfolios as described in the text and winsorized at the 1% and 99% values. Statistical significance is based on a sign rank test of standardized abnormal returns.

			Average Abnormal Returns		
Buy Herding Portfs	Avg # bonds	Average BHM	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B1_VOL	49	10.7%	-0.13%	-0.20% **	-0.28%
B2_VOL	50	32.9%	-0.28% *	0.16%	-0.20%
B3_VOL	50	57.5%	-0.21%	0.01%	-0.17% *
B4_VOL	48	83.0%	-0.28% *	0.15%	-0.17%
B5_VOL	51	99.1%	-0.12%	0.13%	-0.05%
B5_VOL – B1_VOL			0.01%	0.33% **	0.22%
B4_VOL – B1_VOL			-0.14%	0.35% *	0.11%

			Average Abnormal Returns		
Sell Herding Portfs	Avg # bonds	Average SHM	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S1_VOL	64	13.7%	-0.05%	-0.20% **	-0.42% ***
S2_VOL	64	42.4%	-0.15% **	-0.59% ***	-0.16%
S3_VOL	64	70.5%	-0.43% ***	-0.71% ***	-0.39% *
S4_VOL	52	91.7%	-0.70% ***	-0.64% ***	-0.48% ***
S5_VOL	69	99.8%	-1.09% ***	-1.03% ***	-0.62% ***
S5_VOL – S1_VOL			-1.05% **	-0.83% *	-0.19%
S4_VOL – S1_VOL			-0.65% ***	-0.44%	-0.06%

Table 8

Abnormal Returns based on Quoted Prices

Average abnormal returns for 10 portfolios formed in each of 36 quarters from 2003 through 2011. B1_LSV (B5_LSV) consists of bonds with the lowest (highest) LSV buy herding measures during each quarter and S1_LSV (S5_LSV)) consists of bonds with lowest (highest) LSV sell herding measures during each quarter. Portfolios based on the volume based herding measures are defined similarly. Abnormal returns are calculated using the Citi US Broad Investment Grade Bond Index and Citi High Yield Market Index. This approach allows us to classify bonds into five major rating categories (AAA, AA, A, BBB, BB,B, CCC), and then segment these categories into intermediate and long-term indices based upon time to maturity, resulting in 28 matching portfolios. For investment grade bonds, the time to maturity categories are 1 to 3 years, 3 to 7 years, 7 to 10 years, and 10 or more years. For non-investment grade bonds, the categories are 1 to 7 years, 7 to 10 years, and 10 or more years. The abnormal returns are winsorized at the 1% and 99% values. Statistical significance is based on a sign rank test of standardized abnormal returns.

Panel A: LSV Buy Herding	Average Abnormal Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B5_LSV – B1_LSV	0.15%	0.66% **	-0.01%
B4_LSV – B1_LSV	-0.16%	0.51% **	0.13%

Panel B: LSV Sell Herding	Average Abnormal Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S5_LSV - S1_LSV	-0.64% **	-0.45%	0.21%
S4_LSV - S1_LSV	-0.38% ***	-0.11%	-0.12%

Panel C: VOL Buy Herding	Average Abnormal Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B5_VOL – B1_VOL	0.09%	0.38%	-0.12%
B4_VOL – B1_VOL	-0.19%	0.31%	0.10%

Panel D: VOL Sell Herding	Average Abnormal Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S5_VOL - S1_VOL	-0.66% *	-0.42% *	0.09%
S4_VOL - S1_VOL	-0.19%	-0.42% *	0.04%

Table 9

Abnormal Returns Based on Raw Returns

Average returns for 10 portfolios formed in each of 36 quarters from the 2003 through 2011. B1_VOL (B5_VOL) consists of bonds with the lowest (highest) volume based buy herding measures during each quarter and S1_VOL (S5_VOL) consists of bonds with lowest (highest) volume based sell herding measures during each quarter. Returns are winsorized at the 1% and 99% values. Statistical significance is based on a sign rank test of standardized abnormal returns.

Panel A: LSV Buy Herding	Average Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B5_LSV – B1_LSV	-0.20%	0.01% *	0.37%
B4_LSV – B1_LSV	-0.12%	0.03%	0.32%

Panel B: LSV Sell Herding	Average Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S5_LSV - S1_LSV	-0.80% ***	0.08% **	0.92%
S4_LSV - S1_LSV	-0.40% *	-0.25% ***	0.54%*

Panel C: VOL Buy Herding	Average Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B5_VOL – B1_VOL	0.19%	0.36% **	0.35%
B4_VOL – B1_VOL	-0.12%	0.19% **	0.29

Panel D: VOL Sell Herding	Average Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S5_VOL - S1_VOL	-0.51% **	0.07% **	1.06%
S4_VOL - S1_VOL	-0.33%	0.15%	0.61%

Table 10

Abnormal Returns on Portfolios formed Based on Herding Measures for Different Time Periods

Average abnormal returns for difference between portfolios formed in each of 36 quarters from 2002 through 2011. B1 (B5) consists of bonds with the highest (lowest) buy herding measures during each quarter and S5 (S1) consists of bonds with highest (lowest) sell herding measures during each quarter. Panel A use the LSV herding measures and Panel B uses the Volume based herding measures. Abnormal returns are calculated using 34 benchmark portfolios as described in the text. Statistical significance is based on a sign rank test of standardized abnormal returns.

Panel A: Average Abnormal Returns on Portfolios formed using LSV Herding Measures

	Prior to the Fin Crisis ('03-'07)			**During the Fin Crisis** ('08-'09)			After the Fin Crisis ('10-'11)		
	Qtr Prior	Herding Qtr	Qtr After	Qtr Prior	Herding Qtr	Qtr After	Qtr Prior	Herding Qtr	Qtr After
Buy Portf									
B5 – P1	-0.05%	0.23%	0.06%	-0.47%	0.51%	0.66%	-0.27%	-0.39%	0.69%
B4 – P1	0.03%	0.18%	0.09%	-1.13%	-0.16%	0.72%	-0.41%	0.21%	0.67%
Sell Portf									
S5 – S1	-0.81%*	-0.98%**	-0.41%	-3.77%**	1.24%	-0.90%	-1.04%	-0.63%	-0.04%
S4 – S1	-0.30%	-0.36%	-0.19%	-1.84%	-0.93%	1.44%	-0.53%	-1.12%	-0.21%

Panel B: Average Abnormal Returns on Portfolios formed using Volume Based Herding Measures

	Prior to the Fin Crisis ('03-'07)			**During the Fin Crisis** ('08-'09)			After the Fin Crisis ('10-'11)		
	Qtr Prior	Herding Qtr	Qtr After	Qtr Prior	Herding Qtr	Qtr After	Qtr Prior	Herding Qtr	Qtr After
Buy Portf									
B5 – B1	0.02%	0.19%	0.07%	0.17%	0.98%	0.03%	-0.02%	0.22%	0.75%
B4 – B1	0.03%	0.11%	0.02%	-0.60%	1.22%	0.00%	-0.13%	0.30%	0.45%
Sell Portf									
S5 – S1	-0.54%	-0.86%**	-0.17%	-2.58%	-0.29%	-0.02%	-1.31% **	-0.22%	0.07%
S4 – S1	-0.32%	-0.22%	-0.12%	-1.28%	-0.25%	0.34%	-1.16% **	-1.15%	0.04%

Table 11

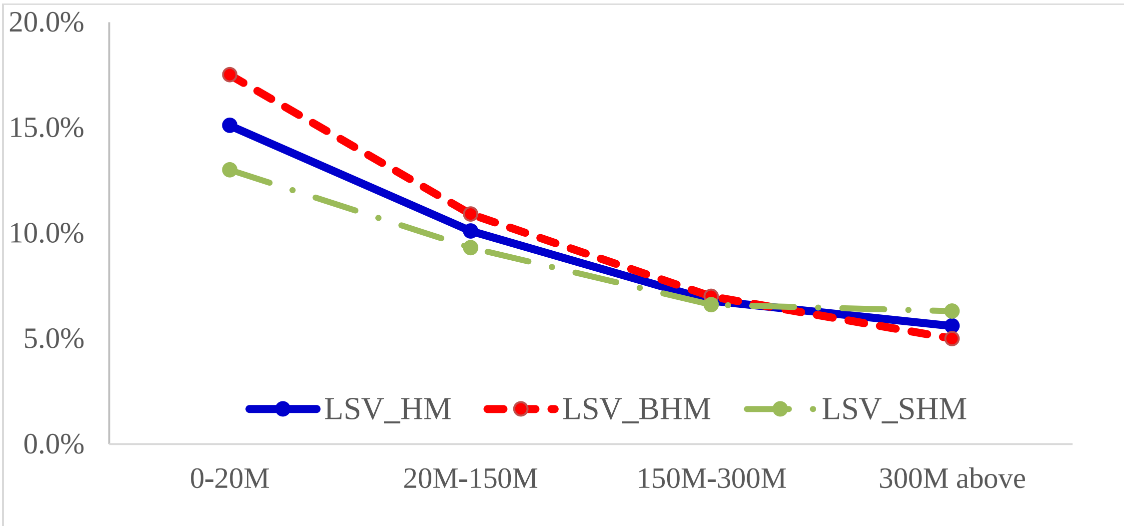
Abnormal returns on bonds in which SIFIs herded

Bonds in the SIFI Group consists of bonds in which at least 15% of the trading volume in the bond during quarter was from insurers that were part of a group that is now classified as a SIFI. All other bonds are in the Non-SIFI Group. Within the SIFI and Non-SIFI Groups, bonds with non-missing buy herding measures based on volume are placed into three portfolios based on their buy herding measures, with BP1 (BP3) being the portfolio with the largest (smallest) buy herding measures based on volume. That is, SP1 (SP3) is the portfolio with the largest (smallest) sell herding measures based on volume.

	Group	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
Buy Portf				
BP3 – BP1	SIFI	-0.17%	0.18%	0.13%*
BP3 – BP1	Non-SIFI	0.01%	0.14%	0.11%
Sell Portf				
SP3 – SP1	SIFI	-0.77%	-1.21%***	-0.67%
SP3 – SP1	Non-SIFI	-0.89%**	-0.35%	-0.00%

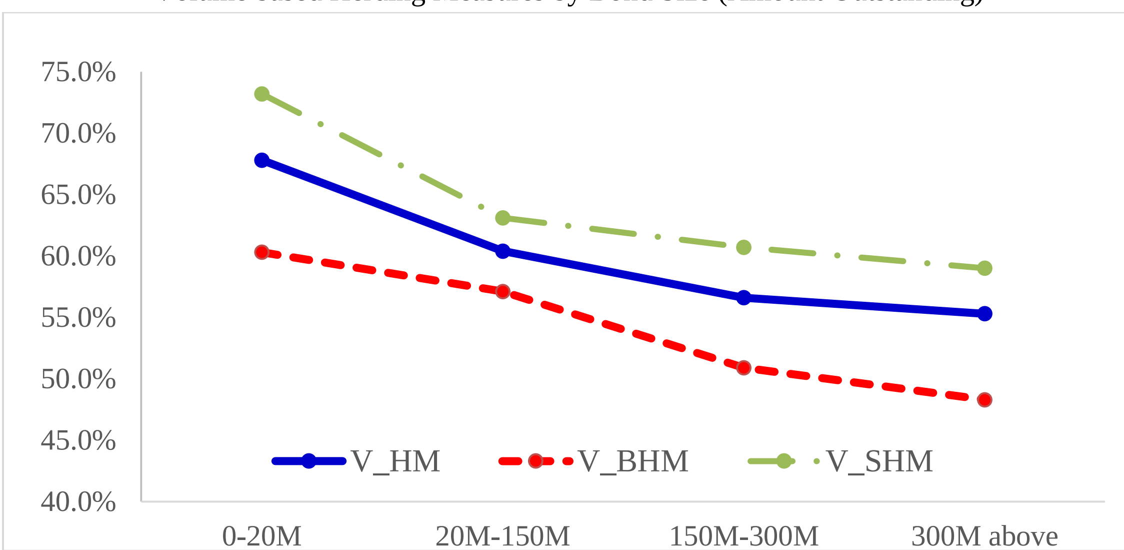
Figure 1

LSV Herding Measures by Bond Size (Amount Outstanding)



N=1,924 N = 16,020 N = 2,267 N = 535

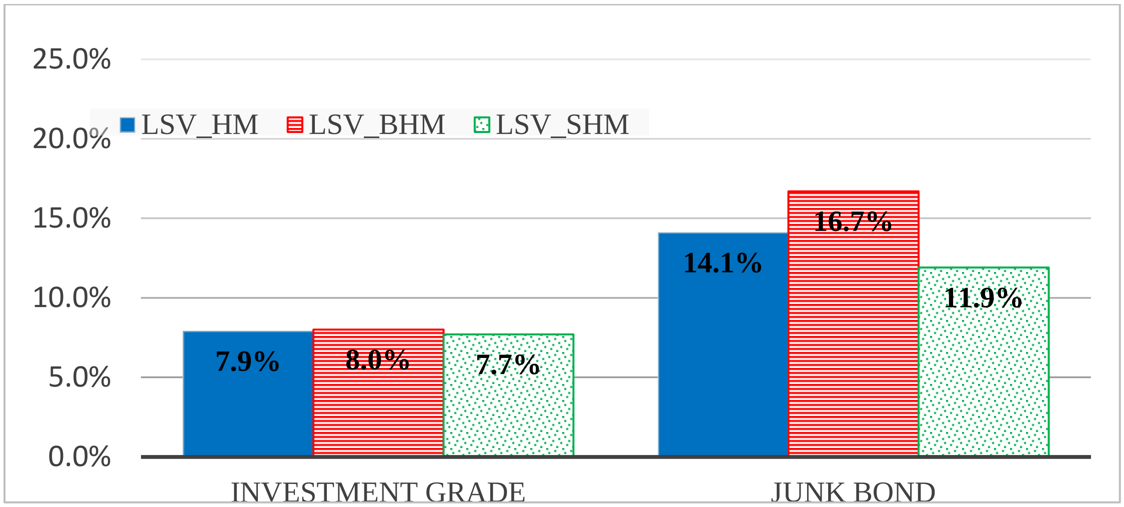
Volume based Herding Measures by Bond Size (Amount Outstanding)



N=1,924 N = 16,020 N = 2,267 N = 535

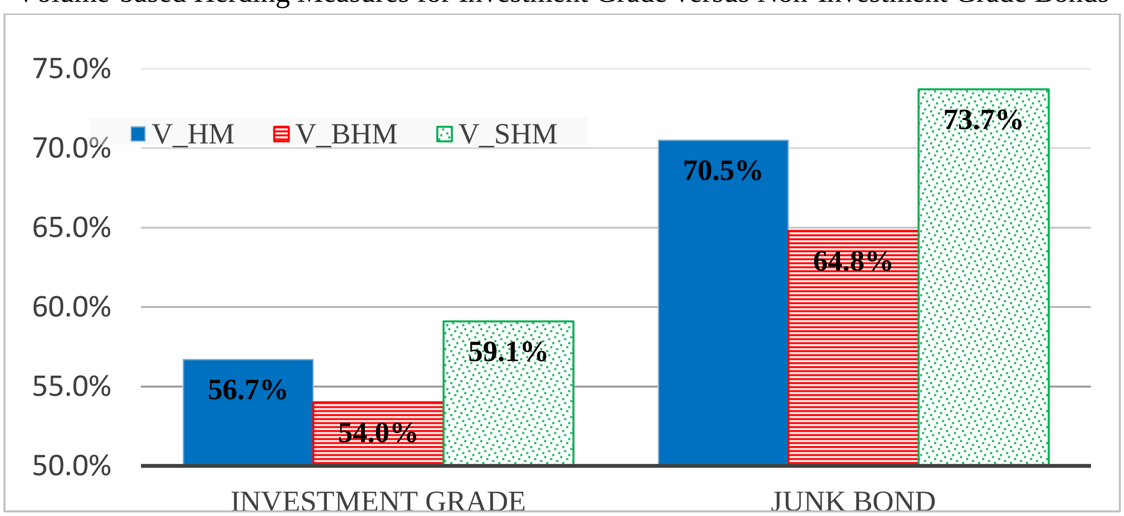
Figure 2

LSV Herding Measures for Investment Grade versus Non-Investment Grade Bonds



N = 14,951 N = 5,785

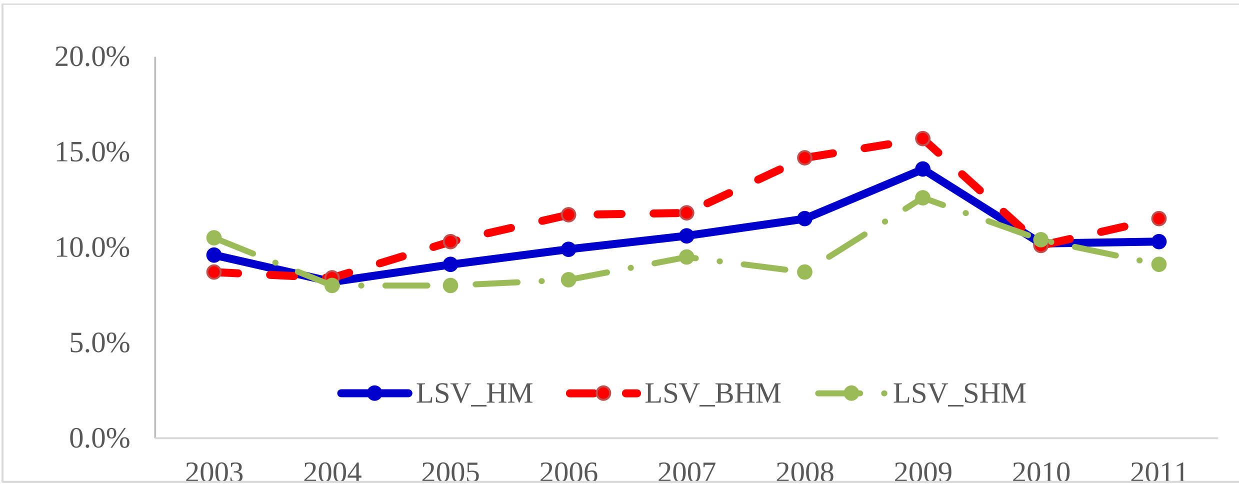
Volume-based Herding Measures for Investment Grade versus Non-Investment Grade Bonds



N = 14,951 N = 5,785

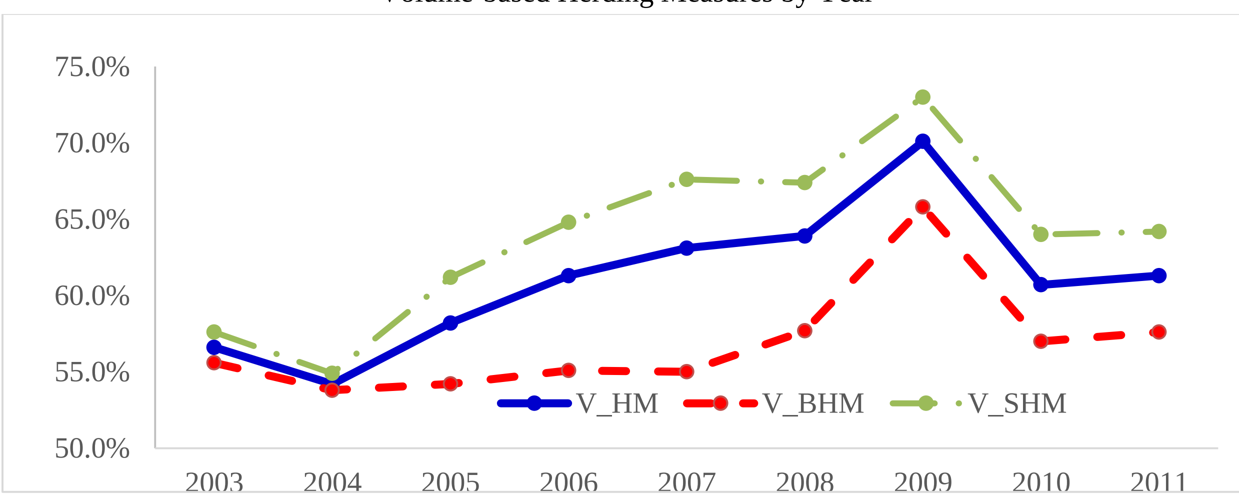
Figure 3

LSV Herding Measures by Year



N=3,254 N=2,819 N=2,826 N=2,642 N=2,035 N=1,766 N=2,351 N=1,710 N=1,357

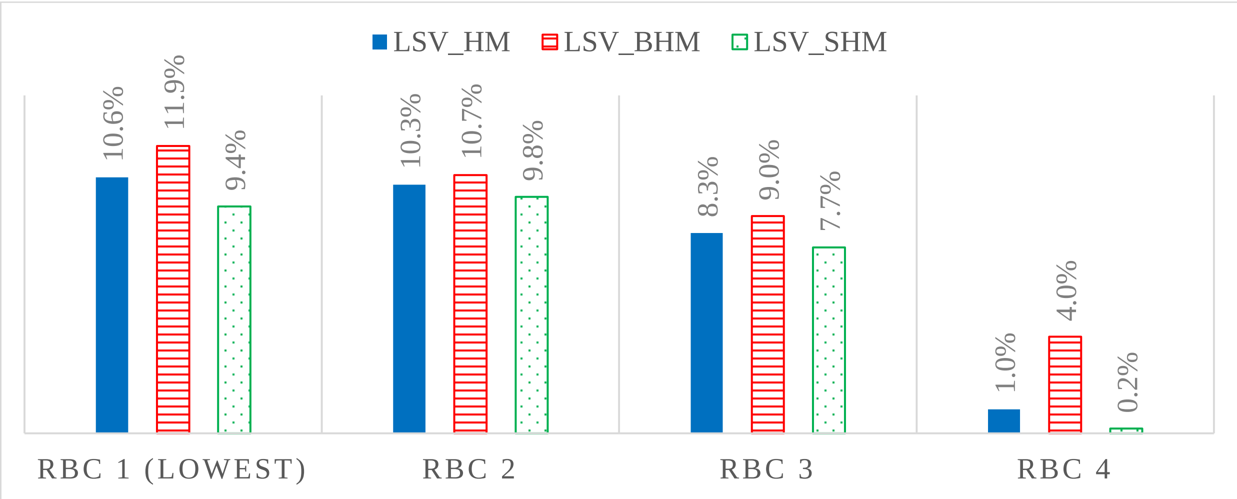
Volume-based Herding Measures by Year



N=3,254 N=2,819 N=2,826 N=2,642 N=2,035 N=1,766 N=2,351 N=1,710 N=1,357

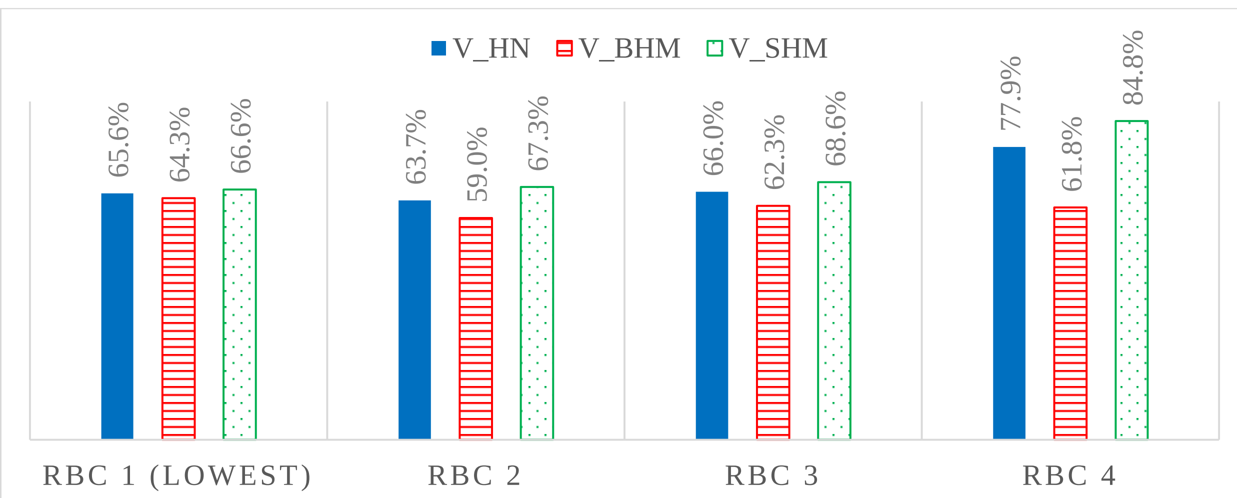
Figure 4

LSV Herding Measures by Average Risk-Based Capital Ratios of Insurers Transacting in the Bonds



N=1,341 N = 4,565 N = 1,428 N = 77

Volume Based Herding Measures by Average Risk-Based Capital Ratios of Insurers Transacting in the Bonds



N=1,341 N = 4,565 N = 1,428 N = 77

Appendix 1 – Calculation of the LSV Herding Measures

To illustrate the LSV measure, suppose that five bonds are in the sample and the deviations of each bond's buy ratio from the overall average buy ratio ($p_{it} – p_t$) equal -0.3, -0.1, 0.1, 0.2, and 0.3. For simplicity, assume the adjustment factor for each security is zero, then the following table would give the herding measures for each of the five bonds and the average herding measures.

Bond	p_{it} - p_t	LSV_HM	LSV_SHM	LSV_BHM
1	-0.3	0.3	0.3	
2	-0.1	0.1	0.1	
3	0.1	0.1		0.1
4	0.2	0.2		0.2
5	0.3	0.3		0.3
Average		0.2	0.2	0.2

The average overall herding measure (LSV_HM) for the sample would be 0.2, the average of the absolute values of the five individual deviations. The average sell herding measure would be 0.2, the average of the absolute values of the two negative deviations; and the average buy herding measure would be 0.2, the average of the three positive deviations.

Appendix 2

Variable definitions

Age_{it} =	bond i's age in years
$AmtOut_{it}$ =	bond i's average of the logarithm of the amount outstanding during quarter t
$Liquidity_{it}$ =	bond i's average Amihud liquidity measure during quarter t
$Rating_{it}$ =	bond i's average rating score during quarter t (1 = AAA, … 10 =default)
$Upgr_{it}$ =	1 if $Rating_{it}$ decreases during quarter t, and 0 otherwise
$Downgr_{it}$ =	1 if $Rating_{it}$ increases during quarter t, and 0 otherwise
$Invgr_{it}$ =	1 if bond i's average rating was above BB in quarter t, and 0 otherwise
$PrRet_{it}$ =	the previous quarter's abnormal return for bond i (see footnote 16)
$\#InsTrans_{it}$ =	natural logarithm of the number of insurers transacting in bond i during quarter t
$PctVol\_SIFI_{it}$ =	the proportion of insurer transaction volume in bond i during quarter t from insurers who are part of a group that has been designated as systemically important,
Avg RBC_{it} =	average risk-based capital ratio of insurers transacting in bond i during quarter t,
Avg ROA_{it} =	average return on assets of insurers transacting in bond i during quarter t,
Avg $LogAssets_{it}$ =	average logarithm of inflation adjusted general account assets of insurers transacting in bond i during quarter t,
Avg $Life\_Foc_{it}$ =	the average value for insurers transacting in bond i during quarter t of a dichotomous variable that equals 1 if an insurer's percentage of premiums written in life insurance exceeds 75 percent, and zero otherwise.
Avg Ann_Foc_{it} =	the average value for insurers transacting in bond i during quarter t of a dichotomous variable that equals 1 if the average percentage of premiums written in annuity exceeds 75 percent, and zero otherwise.
Avg AH_Foc_{it} =	the average value for insurers transacting in bond i during quarter t of a dichotomous variable that equals 1 if the average percentage of premiums written in accident & health insurance exceeds 75 percent, and zero otherwise.