# Investment Herding by Life Insurers

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Abstract:

One of the main arguments for why life insurers are systemically important is that their investment decisions are highly correlated, i.e., that life insurers herd. We analyze U.S. life insurers' investment decisions in corporate bonds from 2002 to 2011 to provide evidence on the extent to which investment activities are correlated across companies within the life insurance industry. Based on investment herding measures from the literature, the results are consistent with life insurers exhibiting herding in corporate bonds, especially in smaller bonds with lower ratings. Moreover, we find herding is more pronounced among insurers with relatively low risk-based capital ratios. While we find evidence of investment herding among life insurers, we do not find evidence indicating that this behavior is likely to be destabilizing to bond markets.

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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 2014 designated MetLife as a systemically important financial institution (SIFI), despite objections from Metlife and other commentators (see e.g., Wallison, 2014). One of the main arguments for why life insurers are a source of systemic risk is that life insurers invest a huge amount of funds in financial securities (especially bonds) and that their trading activity is correlated within the industry, i.e., life insurers herd. As a consequence, life insurers have the potential to disrupt financial markets and either cause or exacerbate a systemic event.[2] Schwarcz and Schwarcz (2014) forcefully make this argument and call for greater regulation.[3]

The counter argument is that even though U.S. life insurers 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,[4] life insurers are typically buy and hold investors; i.e., their trading activity is much lower than their holdings. Therefore, life insurers trading activities are unlikely to impact security prices.[5] Also, while there are examples of life insurer investment behavior impacting security prices, this evidence is for isolated securities, during specific time periods, and by a

[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] 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.
[3] 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.
[4] See McMenamin, et al. (2013) and Campbell and Taksler (2003).
[5] Counter arguments to this argument is that trading in corporate bonds is relatively thin overall, and so even a relatively small amount of trading compared to holdings can potentially impact prices. In addition, a major event (e.g., a run on life insurers) could cause life insurers to have to liquidate assets quickly.

subset of insurers (see the literature discussed in the next section). Currently, there is little research that focuses on the extent to which life insurers' investment decisions are correlated across firms. The purpose of this paper is to fill this gap.

Conceptually, there are several reasons that one might expect herding behavior to exist among life insurers. First, life insurers face common accounting and regulatory rules.[6] 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, a downgrade of a security can increase its risk-based capital requirement, which in turn could provide incentives for insurers 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. The third explanation for herding is referred to as the information cascades theory; it predicts that company fund managers infer the value of securities from the trades of other fund managers, which in turn leads fund managers to mimic other fund managers' trades (Bikhchandani et al., 1992). Fourth, the literature on how the labor market learns about the ability of fund managers implies that fund managers will be concerned about poor performance when other funds have good performance. To avoid this outcome, fund managers will mimic each other (Scharfstein and Stein, 1990).

To investigate whether life insurers' corporate bond investment decisions exhibit herding behavior over the 2002-2011 time period, we calculate herding measures developed by Lakonishok, et al. (1992). These metrics indicate the extent to which insurers tend to buy the same securities or sell the same securities within a given time interval. As is common in the herding literature, we use quarterly time intervals. Our evidence is strongly consistent with life

[6] 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.

insurer herding. The overall herding measure for individual corporate bonds is 9.5 percent on average, which indicates that on average life insurers are about 9.5 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. We also calculate the buy herding and sell herding measures, as proposed by Wermers (1999). The overall buy and sell herding measures for individual corporate bonds have an average value of 9.8 and 9.2 percent, respectively, indicating that the herding by life insurers is not concentrated on one side of the market.

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).[7] Regarding insurer characteristics, we find that herding behavior is greater among insurers that have relatively low risk-based capital ratios on average. Moreover, the relation between herding and risk-based capital ratios is concentrated on the sell side of the market. These findings are consistent with life insurers with relatively low risk-based capital selling downgraded bonds around the same time.

Of course, correlated trading does not necessarily imply that life insurers contribute to systemic risk. While definitive evidence on whether the correlated trading of life insurers is stabilizing or destabilizing to the bond market is difficult to develop, there are 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 correlated trading is

[7] Our results with respect to the impact of bond characteristics on herding by life insurers are similar to those of Cai et al. (2012), who examine determinants of herding by pension funds, mutual funds, and insurance companies (both property-liability and life) combined. Our study differs from Cai et al. (2012) in several respects. We only analyze life insurers; whereas, they do not separately analyze insurers except for reporting the average herding measures by institutional type. Our sample period, is from 2002-2011 and includes the financial crisis; whereas they examine 2003-2008. We use transaction data; whereas, Cai et al. use quarterly holding data. Finally, we investigate the impact of insurer characteristics on herding.

pro-cyclical, i.e., 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 being counter-cyclical, in which case insurer herding is more likely to provide a stabilizing influence on bond markets (Vaughn, 2012).

We provide two types of evidence on whether insurers' trading is pro- or counter-cyclical. In panel regression analysis of herding measures, we find that neither buy nor sell herding measures are significantly related to past abnormal returns, suggesting that herding is neither pro- nor counter-cyclical. Using a different methodology, we analyze the abnormal returns on portfolios of bonds that are selected to have the largest buy and sell herding measures. We do not find that these portfolios have average abnormal returns different from zero in the 90 days prior to the herding behavior. Thus, the evidence does not suggest that herding is pro-cyclical, i.e., the evidence does not indicate that herding is likely to be a destabilizing force on the bond market.

We also examine returns 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. We find little evidence that herding by life insurers is associated with abnormal returns in either the quarter in which the herding behavior takes place or in the subsequent quarter. Thus, herding behavior of life insurers does not appear to have a significant impact on the bond market.

The paper proceeds as follows. In the next section, we review the literature on herding and the investment decisions of life insurers. 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. Some robustness checks are discussed in Section 8. A short summary concludes the paper.

## 2. Related Literature

### 2.1 Theories of Herding and Predictions

There are a number of explanations for why institutional investors might exhibit herding behavior. Institutional factors, such as accounting rules or risk-based capital rules, can cause insurers to trade in similar patterns. Also, if insurers receive the same information at the same time about the value of a bond, then they are likely to transact in the same way (see Froot et al., 1992). Since insurers operating is similar markets and insurers of similar size, capitalization, and profitability are likely to be impacted similarly by economic information as well as by changes in regulatory or accounting policies, we examine the extent to which herding is related to these insurer characteristics.[8] In addition, since insurers are likely to respond to bonds with particular characteristics, in similar ways, we examine whether insurer herding is related to bond characteristics, such as the bond's ratings and whether it was recently downgraded.

The information cascade theory of herding posits that 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 securities issued by small companies is noisier than that of large companies, investors would be more likely to infer information from other institutional investors about the value of small company securities compared to large company securities (see Wermers, 1999 and Sias, 2004). According to this explanation, herding would be most pronounced in bonds of smaller companies.

The information cascade explanation requires that institutions can observe the trading of other institutions. Cai, et al. (2012) present interesting evidence on this issue by examining an exogenous change in the extent to which trading information is revealed to other market participants. Over several phase-in periods between 2002-2005, the Financial Industry Regulatory Authority (FINRA) required that trade information in the corporate bond market be

[8] 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.

made public in real time.[9] Using a difference-in-difference methodology, Cai et al. (2012) show that herding increases in bonds that were subject to the final phase-in period. Their findings are consistent with increased dissemination of trading information increasing the likelihood of mimicking behavior and increasing the likelihood of information cascades. Because of these institutional changes in the corporate bond market and because of changes in economic conditions (e.g., the financial crisis) during our sample period, we incorporate fixed quarter effects in our analysis.

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.[10] Cross-sectional predictions from this framework would relate to managerial-level information, such as manager compensation, age, and experience. Unfortunately, we do not have this type of information.

## 2.2 Empirical Evidence on Herding in Equity Markets

The vast majority of the literature on institutional herding examines equity markets. The one exception is Cai et al. (2012), which we discuss further as we present our results below.[11] The remainder of this section summarizes the evidence from equity markets. The summary is divided in two parts: (1) evidence on herding, and (2) evidence on the relation between herding and prior returns, contemporaneous returns, and subsequent returns.

[9] On July 1, 2002, FINRA required real-time dissemination of a small number of bonds (Phase 1). In March and April of 2003, the list was expanded to over 5,000 bonds (Phase 2). Finally, on October 4, 2004 and February 7, 2005 all over-the-counter bonds except Rule-144A bonds were required to reveal real-time trading information (Phase 3).

[10] Dasgupta et al. (2011) build on this idea in their model of the price impact of herding.

[11] 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. (2009b), who examine clients of two U.S. discount brokers, and Feng and Seasholes (2004), who examine Chinese investors.

Lakonishok, et al. (1992) introduced the herding measures that we use and that most of the herding literature uses. 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. In other words, herding is persistent from one period to the next. Dasgupta et al. (2011) 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. 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. That is, buy (sell) herding is associated with negative (positive) abnormal returns over the subsequent two years. Gutierrez and Kelly (2009) document similar results.

## 2.3 Investment Decisions of Insurers

Recent literature on life insurer investment decisions indicates that insurers with specific characteristics change their investments activities in response to changes in economic or regulatory conditions during specific periods of time. While these papers do not explicitly examine herding, the evidence indicates that a specific set of insurers are buying or selling the same type of security at the same time, consistent with herding behavior.

Insurers "Reach" for Yield. Insurers "reaching for yield" means that insurers exhibit a preference for securities that have higher yields within a rating category. Consistent with this preference, Merrill, et al. (2014a) show that large life insurers that had a relatively high proportion of liabilities from deferred annuities with interest rate guarantees shifted assets out of AAA rated corporate bonds and into AAA rated asset backed securities (ABS) over the 2003 to 2007 period. The ABS securities had yields of about 40 basis points higher than AAA rated corporate bonds. They suggest that this behavior is consistent with these insurers trying to replenish capital after having suffered capital losses due to lower interest rates during this time period.

Also consistent with insurers "reaching for yield," Becker and Ivashina (2013) show that prior to the financial crisis life insurers with relatively low capital were more likely to purchase corporate bonds that had higher promised yields within their NAIC rating category relative to mutual funds and pension funds. They show that these higher yielding bonds did not have higher average returns than comparable bonds. Thus, it appears that these insurers were trying to boost reported earnings (which are based on promised yields) and thus reported capital, without increasing risk-based capital requirements.

Changes in RBC Rules change Insurers' Investments in MBS. Becker and Opp (2014) and Hanley and Nikolova (2014) show that 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. Becker and Opp (2014) show that 92.5% of CMBS purchases were investment grade in the two years prior to the change; whereas, only 47.0% of CMBS purchases were investment grade in the two years after the change. Hanley and Nikolova (2014) find that insurers had a lower probability of selling downgraded MBS after the rule change.

Insurers Sell Downgraded Corporate Bonds. Ambrose, et al. (2008) show that insurers were more likely to sell downgraded bonds than other bonds during the 1995-2006 period, and Ellul et al. (2011) find that insurers with relatively low capital ratios were more likely to sell corporate bonds that were downgraded to non-investment grade during the 2001-2005 period than insurers with higher capital ratios.

In addition, Ellul et al. (2011) find that the downgraded bonds that were sold by insurers exhibited temporary price declines, but prices reverted back to their original levels over the subsequent nine months. The price pattern is consistent with the hypothesis that insurers' trading activity in the downgraded bonds generated price pressure effects due to limited demand for these securities by other institutions, including other insurers. Ellul et al. (2011) provide supplementary evidence consistent with the price pressure explanation. However, Ambrose et al. (2011) provide evidence that the price drop observed for downgraded bonds is due to the downgrade providing information to the market of a lower fundamental value for the bonds, not due to insurers' trading causing price pressure effects.[12]

Downgrades of Asset Backed Securities. During the financial crisis, a number of asset backed securities (ABS) were downgraded, which would lower risk-based capital ratios if insurers continued to hold the downgraded ABS. Consequently, one might expect insurers to sell these securities and put the proceeds in investment grade securities. There is, however, an additional consideration that arises because of the accounting for these securities. Whereas property-liability insurers are required to report securities with NAIC designations 3, 4, 5, or 6 at lower of amortized cost and fair value, life insurers are only required to report securities with an NAIC designation of 6 at lower of amortized cost and fair value. Consequently, following a downgrade that pushes an ABS into a lower NAIC designation (other than category 6), life insurers and property-liability insurers face different tradeoffs. Life insurers, especially those that are poorly capitalized, have a greater incentive to hold downgraded ABS than property-liability insurers. This is because holding the securities has no effect on the numerator of the risk-based capital ratio for life insurers, whereas, holding the securities would lower the numerator for property-liability insurers.

[12] The key feature of Ambrose et al. (2011) analysis is that they separately examine bond downgrades that are associated with stock price declines at the downgrade announcement from downgrades that are not associated with stock price declines at the downgrade announcement. Ellul et al. (2011) also perform a similar analysis and find similar results.

Ellul et al. (2014) examine the trading of life insurers compared to property-liability insurers during the financial crisis and show that life insurers with relatively low capital ratios tended to hold the downgraded ABS compared to property-liability insurers, which tended to sell these securities.  Instead, life insurers were more likely to sell corporate bonds with capital gains, which bolstered their capital ratios because these bonds were previously reported at historical cost or amortized value.[13]

Merrill, et al. (2014) examine the prices at which insurers transacted in RMBS that were downgraded sufficiently to cross a NAIC rating category between 2007 and 2009.  Their evidence is consistent with insurers that experienced operating losses and subject to fair value accounting having an incentive to sell downgraded RMBS at fire sale prices.  Moreover, they show that the RMBS sold at lower prices experienced the largest price reversals following the crisis, after controlling for fundamentals.

Summary.  Existing evidence on life insurer investment decisions provides several reasons why life insurers might exhibit herding behavior. There is evidence that (1) insurers reach for yield prior to the financial crisis and that this behavior was more likely among insurers with low capital or those that experienced negative shocks to capital, (2) insurers alter their investment choices following changes in risk-based capital rules, (3) insurers tend to sell securities that have been downgraded, but less so when the insurers can continue to report the value of those securities at historical costs, and (4) life insurers sold corporate bonds with capital gains to boost capital ratios during the financial crisis.  Thus, existing evidence suggests that for specific securities, under specific conditions, insurers with specific characteristics tend to trade in a consistent pattern.  Moreover the consistent trading of insurers appears to impact prices in some cases.  We now examine whether herding behavior by life insurers is evident more generally in the market for corporate bonds.

[13] Ellul et al. (2014) also provide evidence that the corporate bonds with capital gains that were sold by life insurers underperformed relative to comparable bonds, which is consistent with life insurers' trading activities impacting their prices.

## 3. Methodology

We begin by describing the herding measure for a group of investors that was originally proposed by Lakonishok, et al. (1992). In the following description, the group of investors is a group of insurers, which 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 group that were net buyers of security i during time period t.

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

Of all of the insurers from the group that transacted in security i, the proportion that were net buyers is the insurers' buy ratio for security i:

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

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 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 security 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:

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

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: [14]

$$HM_{i,t} = | p_{i,t} - p_t | - AF_{i,t} ,$$

where

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

and $N_{i,t}$ is the number of insurers transacting in security i during period t. As $N_{i,t}$ increases, the adjustment factor declines.

Intuitively, a positive value for the herding measure indicates that the group of insurers tend to trade a particular security in the same direction more than would be expected if their buy versus sell decisions were independent. By averaging the herding measure 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 determinants of the herding measure.

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

$$\mathrm{BHM_{it}} = \mathrm{HM_{it}} \text{ if } \mathrm{p_{it}} > p_t \text{ and undefined otherwise,}$$

$$\mathrm{SHM_{it}} = \mathrm{HM_{it}} \text{ if } \mathrm{p_{it}} < p_t \text{ and undefined otherwise.}$$

To illustrate, suppose that five securities are in the sample and the deviations of each security'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.

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[14] 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

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

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

| Bond | $p_{it} - p_t$ | HM | SHM | 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 (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.

## 4. Data

We examine insurer transactions in individual bonds over quarterly time periods starting in the fourth quarter of 2002 and ending in the fourth quarter of 2011.[15] 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, there are over 5.4 million bond transactions reported by 1,353 different life insurance companies in 505,654 different bonds issued by 71,434 issuers. 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. After deleting non-market secondary transactions and those observations without a reported cusip or a transaction date, the number of transactions drops to just over 3 million and the number of bonds drops to 429,996.[16]

The transaction data are merged with the Fixed Investment Securities Database (FISD), which provides bond characteristics, including issuance date, maturity date, amount outstanding,

[15] The TRACE data are available starting in the third quarter of 2002. We begin in the fourth quarter of 2002 because there are very few bonds that meet the data requirements in the third quarter.
[16] 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.

coupon rate, and rating history. 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,[17] (d) are corporate bonds denominated in U.S. dollars (because bond characteristics are missing for most of the other bonds).[18] The number of bonds in the sample drops to 23,634 as a result of this step. The data are then merged with the Trade Reporting and Compliance Engine (TRACE) data to obtain liquidity and volume measures (excluding those with absolute daily return greater than 100%), which reduces the number of bonds to 14,707.

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 14,650. We impose the restriction that each bond in the sample in a given quarter must have at least five transactions in the quarter. This gives us 248,020 bond transactions in 6,949 bonds by 906 life insurers. Finally, 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 181,512 bond transactions in 5,364 bonds by 890 life insurers. Recall the herding measures are calculated using all of the transactions by life insurers in a given bond and quarter. There are 20,766 bond-quarter observations (not tabulated).

In Table 2, we present descriptive statistics for the observations that are used in the regression analysis. For this table, we treat each transaction as a separate observation. On average, the bonds transacted have a maturity when issued of 14.1 years, 10.3 years remaining until maturity, and are 3.8 years old. The average (median) face amount is $94 ($65) million. Credit Rating takes a value between one and ten, where one indicates the highest rating (AAA)

[17] The data do not include information about the formula for variable coupon bonds.
[18] This process follows that used by Cai et al. (2012).

and ten is the lowest rating (in default).[19] The average (median) credit rating is 3.9 (4.0) and 70 percent of the bonds transacted have an investment grade rating (i.e., above BB).

Regarding insurer characteristics, we calculate each insurer's risk-based capital ratio and then winsorize at the 1% and 99% levels. The average (median) risk-based capital ratio (RBC) is 8.5 (8.0). The distribution of insurer asset size is skewed with a mean of $39.1 billion and a median of $28.5 billion. Using 75 percent of premiums written in one line of business as an indicator of product line focus, 13 percent of insurers focus in life insurance, 39 percent focus in the annuity business, and 9 percent focus in accident and health insurance.

## 5. Descriptive Analysis of Herding

Table 3 reports the herding measures for the sample described in Table 2. The average herding measure (HM) equals 9.5 percent, which is statistically different from zero. This estimate 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. Also reported in Table 3, the buy herding measure for the overall sample is 9.8 percent and the sell herding measure for the overall sample is 9.2 percent. These results indicate that the herding behavior of life insurers

[19] To calculate a bond's credit rating, we use the average of the four 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 | 1 | 1.1% |
| Above AA | 2 | 6.3% |
| Above A | 3 | 26.4% |
| Above BBB | 4 | 35.1% |
| Above BB | 5 | 15.5% |
| Above B | 6 | 10.5% |
| Above CCC | 7 | 3.0% |
| Above CC | 8 | 0.5% |
| Above C | 9 | 0.3% |
| Default | 10 | 0.5% |
| NR&w | w | 1.0% |

is not concentrated on the buy or sell side of the market. Instead, both buy and sell decisions are correlated across life insurers.[20]

To put these 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 relatively small herding measures for institutional investors' 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. (2012) indicates much higher herding measures, consistent with our results.

Figures 1 – 3 report herding measures for subsets of bonds based on various bond characteristics. 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 1 illustrates that the average herding measures (HM, BHM, and SHM) are highest for bonds with the lowest amount outstanding (between zero and $20 million) and that the average herding measures decline as the face value of the bond 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).[21]

[20] If the entire sample of 100,304 bonds is used, as opposed to those that went through the various data screens outlined in Table 1, the herding measures are higher: HM = 16.3 percent, BHM = 11.1 percent, and SHM = 21.5 percent. The higher SHM than BHM is this broader sample is consistent with Cai et al. (2012).

[21] We also examined whether herding measures are related to bond maturity. If herding is more likely in securities with greater information asymmetry and if longer maturity bonds have greater information asymmetry (see Barnea et al., 1980), then we would expect longer maturity bonds to have higher herding measures. However, we find that the average herding measure is low for bonds with maturity less than or equal to one year and for bonds with maturity greater than 20 years compared to bonds with intermediate maturities.

Figure 2 shows that the average herding measures vary little with the Amihud (2002) liquidity measure. There is, however, a slight U shape in the graph. Cai et al. (2012) find a similar pattern. They suggest that it results from a trade-off between the benefits of information based herding and transaction costs. Illiquid bonds are likely to have greater information asymmetry, thus resulting in greater herding behavior. However, illiquid bonds are more costly to trade, making the herding strategy less profitable. This tradeoff results in very liquid bonds being traded because of low transaction cost and very illiquid bonds being traded because of high private information.

Figure 3 illustrates that the average herding measures are lower for investment grade compared to non-investment grade bonds. In addition, the average buy herding measure is higher than the average sell herding measure for 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. 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.[22]

Figure 4 illustrates how the average herding measures vary over time. For this analysis, the expected buy ratio ($p_t$) is calculated using all of the bonds in the sample, as was done in Table 3. The average herding measures increase gradually from 2004 through 2009. In 2010 and 2011, the average herding measures return to roughly the same level as before the financial crisis. Thus, there is some evidence that herding by insurers increased during the financial crisis.

[22] See Feng and Seasholes (2012) for related arguments.

Figure 5 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 is calculated using all of the bonds traded by the insurers in the risk-based capital category. The four risk-based capital categories are the quartiles of the average risk-based capital ratios of the insurers in the sample. Figure 5 indicates that the insurers with the lowest risk-based capital ratios exhibit the strongest herding behavior.[23]

Finally, Figure 6 presents the average herding measures for insurers with different product line focus. For this analysis, the expected buy ratio is calculated using all of the bonds traded by the insurers with the same product focus. We define an insurer as having a product line focus in life insurance, annuities, or accident & health insurance if the insurer has 75 percent of its premium revenue from one of these lines. Otherwise, we categorize the insurer as not having a focus. Figure 6 indicates that on average the herding measures are higher for insurers with no focus and with an accident and health focus than for insurers with a life insurance and annuity focus.

## 6. Panel Regressions of Herding Measures

We now turn to a panel regression analysis of the bond herding measures. The dependent variable is either the overall herding measure ($HM_{it}$), the sell herding measure ($SHM_{it}$), or the buy herding measure ($BHM_{it}$) for bond i during quarter t. The explanatory variables include

$Age_{it}$ = bond i's age in years,

$AmtOut_{it}$ = bond i's average of the logarithm of the amount outstanding during quarter t,

$Rating_{it}$ = bond i's average rating score during quarter t,

$Liquidity_{it}$ = bond i's average Amihud liquidity measure during quarter t,

$Upgr_{it}$ = 1 if bond i is upgraded at least once during quarter t, and 0 otherwise,

[23] For Figures 5 and 6, 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 used in these Figures and the number of observations across the categories in Figure 5 varies even though the RBC ratios are based on the quartile values.

$Downgr_{it}$ = 1 if bond i is downgraded at least once 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,[24]

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 $LogSize_{it}$ = average logarithm of inflation adjusted general account assets of insurers transacting in bond i during quarter t,

Avg $Focus\_Life_{it}$ = 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 $Focus\_Ann_{it}$ = 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 $Focus\_AH_{it}$ = 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.

The variables can be placed in two categories: (1) bond characteristics and (2) insurer characteristics. Most of the bond characteristics can be considered control variables. The one exception is PrRet, the bond's abnormal return in the previous quarter. A positive (negative) coefficient on PrRet in the buy herding regression would be consistent with herding being pro- (counter-) cyclical on the buy side, i.e., insurers buy after the price has increased (decreased). A positive (negative) coefficient on PrRet in the sell herding measure would be consistent with

[24] The previous quarter return is calculated using the 90 days prior to the first date (denoted F) in which an insurer in the sample transacted in the bond during the quarter and equals $\frac{(P_{i,F-1}+AI_{i,F-1})-(P_{i,F-91}+AI_{i,F-91})+C}{(P_{i,F-91}+AI_{i,F-91})} - \frac{I_{i,F-1}-I_{i,F-91}}{I_{i,F-91}}$,

where $P_{i,F-x}$ is the bond price on day F-x (x days before first transaction by an insurer in the quarter), $AI_{i,F-x}$ is accrued interest on day F-x, and C is the coupon payment(s) received. $I_{i,F-x}$ is the matching portfolio value x days before the first transaction date by an insurer in the quarter. We follow Bessembinder, et al. (2009) and construct matching portfolios (benchmark portfolios) 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, CCC), and then segment these categories into intermediate and long-term indices based upon time to maturity, resulting in 18 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.

herding being counter- (pro-) cyclical, i.e., insurers sell after the price has increased (decreased). 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.

The panel regression results are reported in Table 4. Regarding bond characteristics, the multivariate analysis reinforces some of the relationships found in the univariate analysis in Figures 1 - 4. First, overall herding is greater in smaller bonds, as the coefficient on AmtOutst is negative and statistically significant in the HM regression. Second, as Rating increases (credit risk increases), the overall herding measure increases. A one unit increase in Rating (e.g., a drop from AA to A), increases the herding measure by 0.019 (1.9 percent). However, the regression analysis of the buy and sell herding measures (columns two and three in Table 4) indicate that both the size and rating effects are concentrated on the sell side, as the coefficients on the AmtOutst and Rating are only statistically significant in the sell herding measure (SHM) regression. Thus, insurer sell herding is more likely with smaller bonds with low ratings.

Investment grade bonds exhibit a significantly lower overall herding measure (HM), even after controlling for Rating. The estimated coefficient on InvGr indicates that investment grade bonds have a 0.028 (2.8 percent) lower herding measure on average, controlling for the other factors. The coefficients on UpGr and DownGr give the estimated impact on herding of a change in the bond's rating during the quarter. We do not find a significant effect of upgrades on buy or sell herding measures. Downgrades, however, are associated with a significant increase in the sell herding measure and a significant decrease in the buy herding measure. Moreover, the impact of a downgrade is economically significant, lowering the buy herding measure by 3.5 percent and increasing the sell herding measure by 2.4 percent. There is no relation between downgrades and the overall herding measure, consistent with impact of downgrades on the buy side canceling the impact of downgrades on the sell side. 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 PrRet variable is not statistically significant in any of the regressions. Thus, we do not find evidence of herding being pro- or counter-cyclical using the prior quarter abnormal return.

Regarding insurer characteristics, the panel regressions indicate that larger, more profitable insurers are less likely to engage in herding, especially buy herding. In addition, insurers with higher risk based capital ratios are less likely to engage in herding, especially sell herding. A concern with this regression model is that it imposes a linear relation between herding and the risk-based capital ratio. Differences in risk-based capital ratios are likely to matter less when risk-based capital ratios are relatively high. Therefore, in Table 5, we report the results of an alternative specification that replaces the RBC variable with two dichotomous variables indicating whether the average risk-based capital ratio is less than 7 and between 7 and 9. These cutoffs roughly correspond to the 25$^{th}$ and 75$^{th}$ percentile values for RBC.

We only report the results for the insurer characteristics in Table 5, but all of the other variables are included in the model. The coefficient on the dichotomous variable indicating a risk based capital ratio less than 7 is positive and statistically significant in the overall herding measure regression and in the sell herding measure regression. The coefficient estimates are also economically significant. A low RBC ratio is associated with an increase in the overall herding measure of 1.2 percent and in the sell herding measure of 1.4 percent. This evidence suggests that insurers with low risk-based capital ratios are more likely to exhibit herding behavior.

As a robustness check, we re-estimated the regression models with the lagged herding measure as an additional explanatory variable. This is motivated by Sias (2004) and Dasgupta et al. (2011), who document persistence in herding behavior in equity markets over time. The coefficient on the lagged herding measure is positive and statistically significant at the 10 percent level, consistent with persistence. However, the estimated coefficients on the other explanatory variables remain roughly the same as those reported in Tables 4 and 5.

## 7. Relation between Herding and Bond Abnormal Returns

We further examine whether life insurer herding is pro-cyclical or counter-cyclical using a methodology similar to that employed by Barber et al. (2009) and Dorn et al. (2008) in their studies of equity market herding. This methodology also allows us to examine abnormal bond returns during and subsequent to life insurer herding behavior, 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 insurers having better information about the value of bonds and that their herding incorporates that information into the price of the bonds.
2. 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.
3. 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, which is relieved 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.[25]

[25] The lack of impact does not imply that insurers do not have better information about the value of bonds; it could take longer than the next quarter for the information to be impounded into prices.

For each quarter q, we divide all of the bonds in the sample in two categories: (1) those with a buy ratio greater than the average buy ratio during the quarter and (2) those with a buy ratio less than the average buy ratio during the quarter. Recall, the bonds in the first category are used to construct the buy herding measure and those in the second category are used to construct the sell herding measure. The bonds in the first category are then divided into quintiles (P1 to P5) based on the magnitude of their buy-herding measures (BHM). Portfolio P1 consists of the bonds with the highest buy herding measures in each quarter. We repeat the same rank procedure for bonds with sell-herding measures, creating portfolios P6 to P10, where portfolio P10 represents the portfolio of bonds with the highest sell herding measures in each quarter.

The first three columns of Table 6 provide descriptive information about the average number of bonds in each portfolio and the average herding measure (buy herding measure for portfolios P1-P5 and the sell herding measure for portfolios P6-P10) over the sample period.[26] The average herding measure in Portfolio 1 is 33.7 percent and the average herding measure in Portfolio 10 is 31.0 percent, both of which suggest a substantial degree of herding in the bonds in these portfolios. Portfolios 2 and 9 have average herding measures of 18.7 percent and 20.0 percent, respectively; these numbers also suggest a high degree of herding in the bonds in these portfolios. In contrast, portfolios 4, 5, 6, and 7 have herding measures that are negative, indicating little herding in the bonds in these portfolios.

For each of these 10 portfolios and for each of the 37 quarters, we calculate the equally-weighted abnormal returns for the quarter before, the quarter of, and the quarter after the portfolio formation quarter. As described in an earlier footnote, the abnormal returns are calculated using the matching portfolio methodology in Bessembinder, et al. (2009). For a given bond and quarter, let F equal the first transaction date by an insurer in the bond and L equal the last transaction date in the quarter by an insurer in the bond. Then the abnormal return is

[26] 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.

calculated for the time intervals: [F-91,F-1], [F,L], and [L+1,L+91].[27] This is repeated for each bond in the portfolio in the 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 37 quarters to calculate the overall average abnormal return for each of the 10 portfolios.[28,29]

Table 6 reports the overall average abnormal returns for each of the 10 portfolios. We focus on the portfolios with the largest herding measures: P1, P2, P9, and P10. Consider first the abnormal returns in the quarter prior to the portfolio formation. The -0.9 percent abnormal return for P1 is large in economic terms and is consistent with counter-cyclical buy herding. However, it is not statistically significant. The bonds in portfolio P2 are not associated with a significant average abnormal return in the quarter prior to the buy herding. Similarly, the bonds with the most extreme sell herding measures (P10) are not associated with a significant average abnormal return in the prior quarter. However, the bonds in P9 on average performed poorly in the prior quarter as they earned a -0.7 percent abnormal return, which is significantly different from zero at the 10 percent level. The results for P9 are consistent with pro-cyclical herding (sell herding following price declines). Thus, the results for the prior quarter abnormal returns provide some evidence of pro-cyclical and some evidence of counter-cyclical herding by life insurers, but neither piece of evidence is strong.

For the quarter in which the portfolios are formed, the buy herding portfolios all have negative abnormal returns, but none of the abnormal returns is significantly different from zero.

[27] 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 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. Only about seven percent of the days for which we seek a price have a transaction on that day. In 49 percent of the other days, a transaction price is found in the prior 30 days, but in about 51 percent of the other cases, we need to go back more than 30 days to find a transaction price.

[28] The appendix describes the results of an alternative method that calculates average abnormal returns over the 90 days prior to each trade in the portfolio formation quarter and 90 days subsequent to each trade of each quarter.

[29] The statistical significance of the overall average abnormal returns is based on the assumption that the portfolio average abnormal return in one quarter is independent of the average abnormal return in the other quarters. An alternative assumption would be to treat the abnormal returns of each individual transaction as being independent. Because the latter approach would ignore the clustering of event windows in a given calendar period, we report significance using the former approach. The appendix presents the results using the latter approach.

Similarly, none of the abnormal returns for the sell herding portfolios is significantly different from zero. Finally, consider the quarter subsequent to the portfolio formation quarter. Neither of the extreme buy herding portfolios (P1 and P2) and neither of the extreme sell herding portfolios (P10 and P9) exhibit abnormal returns. In summary, the results regarding abnormal returns in the quarter in which herding occurs and in the quarter after herding occurs do not indicate that insurer herding has a consistent impact on the bond prices.

## 8. Robustness Checks

Taking into Account the Amount Traded. The herding measures used in the paper 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 $5 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:

$$| \text{Amount Purchased}_{it} – \text{Amount Sold}_{it} | / [ \text{Amount Purchased}_{it} + \text{Amount Sold}_{it} ].$$

In addition to taking into account the amount sold, the herding measure based on volume differs from the herding measures based on the number of trades in that it does not subtract a benchmark measure of insurer buy versus sell volume in the bond market. Thus, unlike the earlier measures, this is not a measure of insurer trading in a particular bond relative to insurer trading in the bond market.

To form portfolios of bonds with common values for the herding measure based on volume, we first consider the bonds for which insurers' buy volume is greater than their sell volume. We place these bonds info five portfolios using on the herding measured based on volume. Portfolio P1 has the bonds with the highest herding measures based on volume and portfolio P5 has the bonds with the lowest measures. We then do the same process for the bonds with insurer sell volume greater than buy volume. Portfolio P10 has the highest herding measure based on volume and portfolio P6 has the bonds with the lowest measures.

Table 7 presents the average values of the herding measure based on volume for each of the portfolios and the average abnormal returns in the quarter prior to, during, and subsequent to portfolio formation. As with the earlier analysis, we focus on portfolios P1, P2, P9, and P10. The portfolio with the bonds with the largest buy herding measures based on volume, P1, has a -1.2 percent abnormal return in the quarter prior to portfolio formation and it is statistically different from zero at the 5 percent level. This is consistent with counter-cyclical herding. Portfolio P9, which has the second largest sell herding measure based on volume, has a statistically and economically significant -1.1 percent abnormal return in the quarter prior to portfolio formation, which is consistent with pro-cyclical herding. Thus, there is some evidence that insurers are buying bonds that have recently performed poorly and also selling bonds that have recently performed poorly. These results are similar to those presented earlier with the herding measures based on trades.

Now consider the quarter during and after portfolio formation. One difference between the results in Table 7 and the earlier results is that portfolio P9 has negative and statistically significant abnormal returns during the portfolio formation quarter, which is consistent with insurer sell herding impacting the market price.[30] Consistent with the earlier analysis, none of the other extreme herding portfolios (P1, P2, and P10) exhibit significant abnormal returns during the herding quarter or subsequent to the herding quarter. Overall (and consistent with the earlier analysis), the results do not provide strong evidence that insurer trading has a consistent impact on the bond market.

Group versus Company Herding Measures. The herding measures reported throughout the paper are calculated using company level data. Thus, if two companies in the same group

[30] Although we do not focus attention on Portfolio P8, it is worth noting that it also has negative and statistically significant abnormal returns during the portfolio formation quarter. The negative abnormal returns continue in the subsequent quarter for P8, which is consistent with insurers having information about the value of the bonds that is slowly impounded into the price and inconsistent with the price pressure explanation.

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, these two transactions should be consolidated and treated as one buy transaction, which would result in lower 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 more accurately reflect the extent to which independent organizations herd.

Table 8 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 consolidated herding measures are about half the magnitude of those reported in Table 3. For example, the average overall herding measure reported earlier is 9.5 percent and the one reported in Table 8 is 5.4 percent. Note that the number of bonds used to calculate the average herding measures in Table 8 is substantially lower than the number of bonds used to calculate the average herding measures reported in Table 3. The reason for this 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 8 but do not consolidate transactions of insurers in the same group, then average herding measures are roughly midway between those reported in Table 8 and those reported in Table 3. For example, the average overall herding measure for the bonds in Table 8 without consolidation equals 7.7 (compared to 5.4 in Table 8).

More importantly, the cross-sectional and time series patterns in the herding measures reported earlier in the regression analysis are not changed substantially if we use the consolidated herding measures. In addition, the analysis of the abnormal returns for the decile portfolios formed using the consolidated herding measures are similar to those reported in Table 6.

## 9. Summary

Using traditional 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, 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. This behavior is more pronounced in smaller bonds and lower rated bonds, and is more pronounced among insurers with relatively low risk-based capital ratios.

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 presented here 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 an impact on market prices. Thus, we also examine the relationship between herding behavior and both previous and subsequent abnormal returns. We do not find strong associations between herding behavior and abnormal returns in the quarter before, during, or after life insurer herding behavior. In other words, there is little evidence that life insurer herding is responsive to the market or impacts the market. This evidence lessens concerns about herding behavior of life insurers contributing to systemic risk.

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## Appendix

An alternative method for calculating abnormal returns is to use the 90 days prior to and subsequent to each insurer transaction in the portfolio formation quarter, as opposed to the 90 days prior to the first insurer transaction and the 90 days subsequent to the last insurer transaction in the portfolio formation quarter. Let t equals the transaction date for an insurer in a particular bond and quarter. The abnormal return for this bond is calculated for the time intervals: [t-91,t-1], [t-1,t], and [t+1,t+91]. This is repeated for each insurer transaction in that bond during that quarter and the resulting values are averaged to calculate the average abnormal returns for each of the three time interval for that bond and quarter. This is done for each bond in each of the P1 –P10 portfolios during each quarter. These quarterly average abnormal returns are then averaged over bonds in the portfolio and over the 37 quarters to calculate the overall average abnormal return for each of the 10 portfolios.

Table A1 reports the results. The bonds in portfolios P1 and P2 are not associated with a significant average abnormal return in the quarter prior to the buy herding. Similarly, the bonds with the most extreme sell herding measures (P9 and P10) are not associated with a significant average abnormal return. Overall, the results for the prior quarter abnormal returns do not suggest strong pro- or counter- cyclical herding by life insurers.

For the two days around the insurer transactions, the extreme buy herding portfolios (P1 and P2) and the extreme sell herding portfolios (P9 and P10) all have abnormal returns that are not significantly different from zero.

Finally, consider the quarter subsequent to the insurer transactions. The extreme buy herding portfolio (P1) shows a negative and significant average abnormal return equal to -0.9%. The extreme sell herding portfolio (P10) shows a positive and significant average abnormal return equal to 1.6%.

Table A1

Abnormal Returns on Portfolios formed Based on Herding Measures

Using an Alternative Method for Calculating Abnormal Returns

Average abnormal returns for 10 portfolios formed in each of 37 quarters from the 4th quarter of 2002 through 2011. Portfolio 10 consists of bonds with the highest buy herding measures during each quarter and Portfolio 1 consists of bonds with highest sell herding measures during each quarter. Abnormal returns are calculated using 18 benchmark portfolios as described in the text. Time t is the date of an insurer's transaction in the bond during the portfolio formation quarter. The abnormal return associated with each transaction is averaged to find the average for the quarter and these are then averaged over the 37 quarters.

| Portfolio | Average # of bonds | Average BHM/SHM | Avg Abn Ret [t-91,t-1] | Avg Abn Ret [t-1,t] | Avg Abn Ret [t+1,t+91] |
|---|---|---|---|---|---|
| P1 | 55 | 33.7% | -0.6% | -0.5% | -0.9% * |
| P2 | 57 | 18.7% | -0.8% | 0.1% | 1.0% |
| P3 | 56 | 8.6% | -1.1% ** | -0.4% | -0.7% |
| P4 | 55 | -1.3% | -0.3% | -0.1% | -1.0% ** |
| P5 | 57 | -9.8% | -0.3% | -0.7% * | -0.7% |
| P6 | 56 | -10.8% | -0.5% | -0.8% ** | -1.4% ** |
| P7 | 56 | -1.3% | -0.6% ** | -0.9% ** | -1.5% ** |
| P8 | 58 | 8.5% | -0.8% * | -1.1% ** | -1.7% *** |
| P9 | 56 | 20.0% | -0.5% * | -0.5% | -1.2% ** |
| P10 | 55 | 31.0% | 0.6% | 0.5% | 1.6% * |
| P1-P10 | | | -1.2% | -1.0% | -0.5% |

Table 1
Sample Selection Process

| Step | Total Sample | Bond Transactions | Bond Issues | Bond Issuers | Insurance Companies |
|---|---|---|---|---|---|
| 1 | Life Insurer bond transactions from 2002-2011 | 5,464,804 | 505,654 | 71,434 | 1,353 |
| 2 | After deleting obs. with no cusip, no transaction date, and non-secondary market trades | 3,071,684 | 429,996 | 56,428 | 1,338 |
| 3 | Merged with FISD & require<br>- maturity >2 quarters<br>- age > 3 quarters<br>- fixed coupon<br>- corporate bond | 731,457 | 23,634 | 6,399 | 1,118 |
| 4 | Merged with TRACE liquidity | 484,448 | 14,707 | 4,083 | 1,006 |
| 5 | Merged with Insurer Capitalization data | 466,111 | 14,650 | 4,078 | 943 |
| 6 | Require 5 transactions per quarter | 248,020 | 6,949 | 2,431 | 906 |
| 7. | Merged with previous returns | 181,512 | 5,364 | 1,767 | 890 |

Table 2
Characteristics of Bonds and Insurers in the Sample

Maturity is the number of years until the bond matures. Bond Life is the number of years that the bond has existed. Face amount is the face amount of the bond ($millions). Credit Rating is the average of the S&P, Moody's, Fitch, and Duff & Phelps ratings and takes a value between 1 and 10 with 1 being AAA, 2 above AA, etc. Investment grade is equal to one if the bond is investment grade (rating above BB) and zero otherwise. Amihud Liquidity is the measure of liquidity in Amihud (2002). RBC is the insurer's risk-based capital ratio, winsorized at the 1 and 99 percentile values. Assets is the insurer's total assets ($billions). LogAssets is the natural logarithm of total assets. Life Bus > 75% equals one if the percentage of premiums written from life insurance exceeds 75 percent and zero otherwise. Ann Bus > 75% equals one if the percentage of premiums written from annuities exceeds 75 percent and zero otherwise. 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 20,766 transactions in 5,364 bonds by 890 life insurers.

| Bond Characteristics | Var Name | Mean | Median | Min | Max | Stdev |
|---|---|---|---|---|---|---|
| Maturity when issued (yrs.) | | 14.1 | 10.0 | 1.8 | 100.0 | 9.1 |
| Remaining Bond Life (yrs) | | 10.3 | 7.3 | 0.5 | 94.6 | 8.6 |
| Bond Age (yrs) | Age | 3.8 | 3.1 | 0.8 | 24.3 | 2.7 |
| Face Amount ($mill) | AmtOutst | 94.0 | 65.0 | 0.0 | 736.3 | 84.8 |
| Credit Rating | Rating | 3.9 | 4.0 | 1.0 | 10.0 | 1.2 |
| Investment Grade | InvGr | 0.7 | 1.0 | 0.0 | 1.0 | 0.4 |
| Upgraded (in %) | UpGr | 3.1 | 0.0 | 0.0 | 100 | 17.4 |
| Downgraded (in %) | DownGr | 7.6 | 0.0 | 0.0 | 100.0 | 26.5 |
| Prior qtr Return (in %) | PrRet | -0.9 | -1.1 | -100.0 | 100.0 | 12.3 |
| Amihud Liq. measure | Liquidity | 1.2 | 0.4 | 0 | 1,838.7 | 22.3 |
| | | | | | | |
| Insurer Characteristics | | | | | | |
| Avg Risk-Based Capital Ratio | RBC | 8.5 | 8.0 | 2.1 | 110.9 | 3.2 |
| Avg Return on Assets (in %) | ROA | 0.9 | 0.9 | -33.3 | 28.0 | 2.1 |
| Avg value of Assets ($billions) | | 39.1 | 28.5 | 0.05 | 212.00 | 34.1 |
| LogAssets | LogAssets | 23.5 | 23.6 | 17.4 | 26.2 | 1.0 |
| Life Bus > 75% | | 0.13 | 0.04 | 0.00 | 1.00 | 0.19 |
| Ann Bus > 75% | | 0.39 | 0.36 | 0.00 | 1.00 | 0.29 |
| A&H Bus > 75% | | 0.09 | 0.02 | 0.00 | 1.00 | 0.15 |

Table 3

Herding Measures

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

| Variable | N | Mean | StdDev | P-value |
|---|---|---|---|---|
| HM | 20,766 | 9.5% | 15.5% | <.0001 |
| BHM | 10.365 | 9.8% | 15.7% | <.0001 |
| SHM | 10,401 | 9.2% | 15.3% | <.0001 |

Panel B: Representative Results from Prior Literature on Institutional Herding Measures

| Reference | Institutions | Securities | Time Period | Mean HM | Mean BHM, 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. (2012) | Insurers | Corp bonds | ’03-‘08 | 9.8% | 8.8% , 1.1% |
| | Mutual funds | Corp bonds | ’03-‘08 | 8.6% | 8.3% , 8.9% |
| | Pension funds | Corp bonds | ’03-‘08 | 6.4% | 8.3% , 8.9% |

Table 4

Panel Regressions for Herding Measures

Dependent variable is the herding measure (HM), buy herding measure (BHM), or sell herding measure (SHM) for bond i during quarter t. 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; Liquidity = average Amihud liquidity measure; Upgr = 1 if bond is upgraded at least once during quarter, and 0 otherwise; Downgr = 1 if bond is downgraded at least once during quarter, and 0 otherwise; Invgr = 1 if bond's average rating was above BB in quarter, and 0 otherwise; PrRet = the previous quarter's abnormal return for bond i. The following characteristics of the insurers transacting in bond i during quarter t are included: Avg RBC = average risk-based capital ratio; Avg ROA = average return on assets; and Avg LogSize = average logarithm of inflation adjusted general account assets. Also included in the regressions are the variables Avg Focus_Life, Avg Focus_Ann, and Avg Focus_A&H, which 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.

Table 4 (continued)

| | HM | BHM | SHM |
|---|---|---|---|
| Age | -0.005 | -0.012 | 0.035 |
| | (0.029) | (0.053) | (0.047) |
| AmtOutst | -0.074 *** | -0.016 | -0.067 *** |
| | (0.016) | (0.037) | (0.019) |
| Rating | 0.019 *** | -0.000 | 0.017 *** |
| | (0.004) | (0.008) | (0.005) |
| Liquidity X $10^5$ | 2.349 | 8.39 | -5.374 |
| | (5.042) | (6.367) | (4.934) |
| UpGr | 0.014* | 0.013 | 0.010 |
| | (0.008) | (0.014) | (0.013) |
| DownGr | 0.003 | -0.035 *** | 0.024 *** |
| | (0.006) | (0.012) | (0.008) |
| InvGr | -0.028 *** | -0.026 | -0.022 * |
| | (0.008) | (0.017) | (0.013) |
| PrRet X $10^5$ | 7.978 | 13.015 | -7.055 |
| | (9.429) | (14.79) | (18.56) |
| Avg RBC | -0.001 ** | -0.001 | -0.002 ** |
| | (0.001) | (0.001) | (0.001) |
| Avg ROA | -0.159 ** | -0.329 ** | -0.087 |
| | (0.080) | (0.146) | (0.123) |
| Avg LogSize | -0.005 *** | -0.008 *** | -0.001 |
| | (0.002) | (0.003) | (0.003) |
| Avg Focus_Life | -0.003 | 0.003 | -0.007 |
| | (0.008) | (0.014) | (0.013) |
| Avg Focus_Ann | 0.002 | -0.009 | 0.008 |
| | (0.006) | (0.010) | (0.009) |
| Avg Focus_AH | 0.015 | 0.027 | 0.016 |
| | (0.012) | (0.019) | (0.019) |
| Constant | 1.146 *** | 0.543 | 0.925 *** |
| | (0.225) | (0.512) | (0.269) |
| Quarter FE | Yes | Yes | Yes |
| Bond FE | Yes | Yes | Yes |
| $R^2$ | 0.344 | 0.473 | 0.509 |
| N | 20,765 | 10,365 | 10,400 |

Table 5

Panel Regressions for Herding Measures

Dependent variable is the herding measure, buy herding measure, or sell herding measure for bond i during time t ($HM_{it}$, $BHM_{it}$, or $SHM_{it}$). The explanatory variables are the same as in the previous table, except RBC is replaced with two dichotomous variables indicating whether the risk-based capital ratio is less than 7 (roughly the 25th percentile value) and between 7 and 9 (roughly the 75 percentile value). Only the coefficient on these two variables are reported. 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.

| | HM | BHM | SHM |
|---|---|---|---|
| RBC < 7 | 0.012 *** | 0.012 | 0.014 * |
| | (0.005) | (0.008) | (0.008) |
| 7 ≤ RBC ≤ 9 | 0.006 * | 0.010 * | 0.007 |
| | (0.004) | (0.006) | (0.006) |
| Quarter FE | Yes | Yes | Yes |
| Bond FE | Yes | Yes | Yes |
| $R^2$ | 0.344 | 0.474 | 0.509 |
| N | 20,765 | 10,365 | 10,400 |

Table 6

Abnormal Returns on Portfolios formed Based on Herding Measures

Average abnormal returns for 10 portfolios formed in each of 37 quarters from the 4th quarter of 2002 through 2011. Portfolio 10 consists of bonds with the highest buy herding measures during each quarter and Portfolio 1 consists of bonds with highest sell herding measures during each quarter. Abnormal returns are calculated using 18 benchmark portfolios as described in the text. Abnormal returns for each bond are calculated based on the first date that the bond was traded in the quarter, F, and the last date that the bond was traded in the quarter, L.

| Portfolio | Average # of bonds | Average BHM/SHM | Avg Abn Ret [F-91,F-1] | Avg Abn Ret [F,L] | Avg Abn Ret [L+1,L+91] |
|---|---|---|---|---|---|
| P1 | 55 | 33.7% | -0.9% | -0.3% | -0.3% |
| P2 | 57 | 18.7% | 0.0% | -0.6% | 0.3% |
| P3 | 56 | 8.6% | -0.8% ** | -0.6% | -0.2% |
| P4 | 55 | -1.3% | -0.3% | -0.4% | -0.5% |
| P5 | 57 | -9.8% | 0.0% | -0.3% | -0.5% |
| | | | | | |
| P6 | 56 | -10.8% | -0.7% | -0.4% | -0.8% ** |
| P7 | 56 | -1.3% | -0.8% * | -0.2% | -1.2% *** |
| P8 | 58 | 8.5% | -0.6% | -0.3% | -0.9% * |
| P9 | 56 | 20.0% | -0.7% * | -0.2% | -0.7% |
| P10 | 55 | 31.0% | 0.2% | 0.3% | 0.2% |
| | | | | | |
| P1-P10 | | | -1.1% | | -0.5% |

Table 7

Abnormal Returns for Portfolios formed using Herding Measure Based on Insurer Volume

Average abnormal returns for 10 portfolios formed in each of 37 quarters from the 4th quarter of 2002 through 2011. Portfolio 10 consists of bonds with the highest herding measures (HM) based on volume for bonds that have greater insurer buy volume than sell volume. Portfolio 1 consists of bonds with the highest herding measures based on volume for bonds that have greater sell volume than buy volume. Abnormal returns are calculated using 18 benchmark portfolios as described in the text. Abnormal returns for each bond are calculated based on the first date that the bond was traded in the quarter, F, and the last date that the bond was traded in the quarter, L.

| Portfolio | Average # of bonds | Avg HM Based on Volume | Avg Abn Ret [F-91,F-1] | Avg Abn Ret [F,L] | Avg Abn Ret [L+1,L+91] |
|---|---|---|---|---|---|
| P1 | 55 | 99.0% | -1.2% ** | -0.5% | -0.4% |
| P2 | 57 | 82.1% | -0.1% | -0.0% | 0.1% |
| P3 | 60 | 57.7% | -0.5% | -0.5% | -0.5% |
| P4 | 61 | 33.5% | 0.1% | -0.6% ** | 0.1% |
| P5 | 59 | 10.7% | -0.1% | -0.2% | -1.0% *** |
| P6 | 74 | 12.9% | -0.9% ** | -0.2% * | -0.5% |
| P7 | 76 | 41.4% | -1.0% ** | 0.0% | -1.1% *** |
| P8 | 76 | 70.1% | -0.3% | -0.8% *** | -1.1% *** |
| P9 | 60 | 91.3% | -1.1% *** | -0.6% * | -0.2% |
| P10 | 65 | 99.9% | -0.1% | 0.1% | 0.3% |
| P1-P10 | | | -1.1% | -0.6% | -0.7% |

Table 8

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

Overall Herding Measures for Sample of Insurers transacting in Corporate Bonds
from 2002-2011 when transactions of insurers in the same group are consolidated

| Variable | N | Mean | StdDev | P-value |
|---|---|---|---|---|
| HM | 12,641 | 5.4% | 14.3% | <.0001 |
| BHM | 6,346 | 5.4% | 14.0% | <.0001 |
| SHM | 6,295 | 5.3% | 14.6% | <.0001 |

Figure 1

Herding Measures by Bond Size (Amount Outstanding)

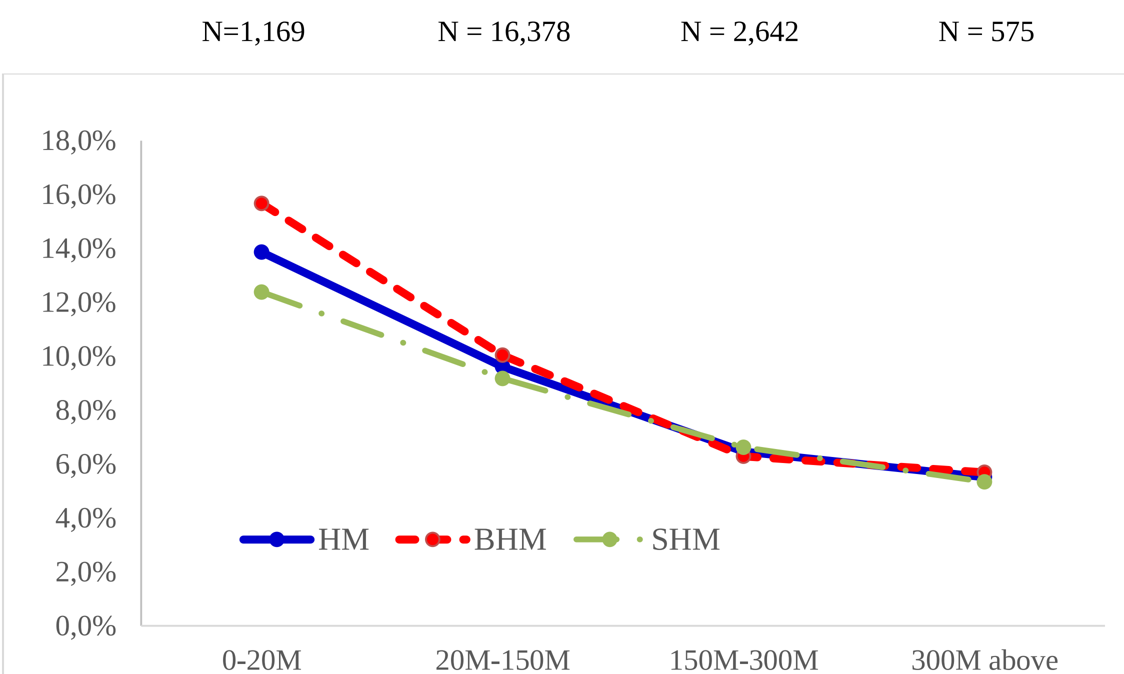



Figure 2

Herding Measures by Liquidity Quintile (Amihud, 2002)

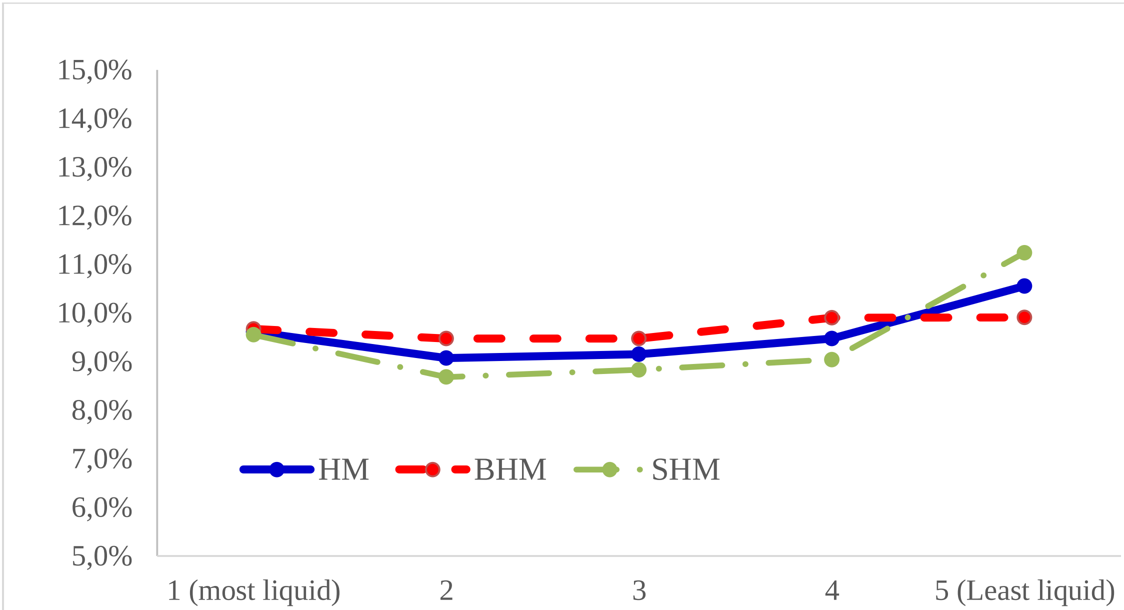



Figure 3

Herding Measures for Investment Grade versus Non-Investment Grade Bonds


N = 15,577 N = 5,165

Figure 4

Herding Measures by Year

N=2.539 N = 6,981 N = 6,772 N = 3,474 N = 1,000

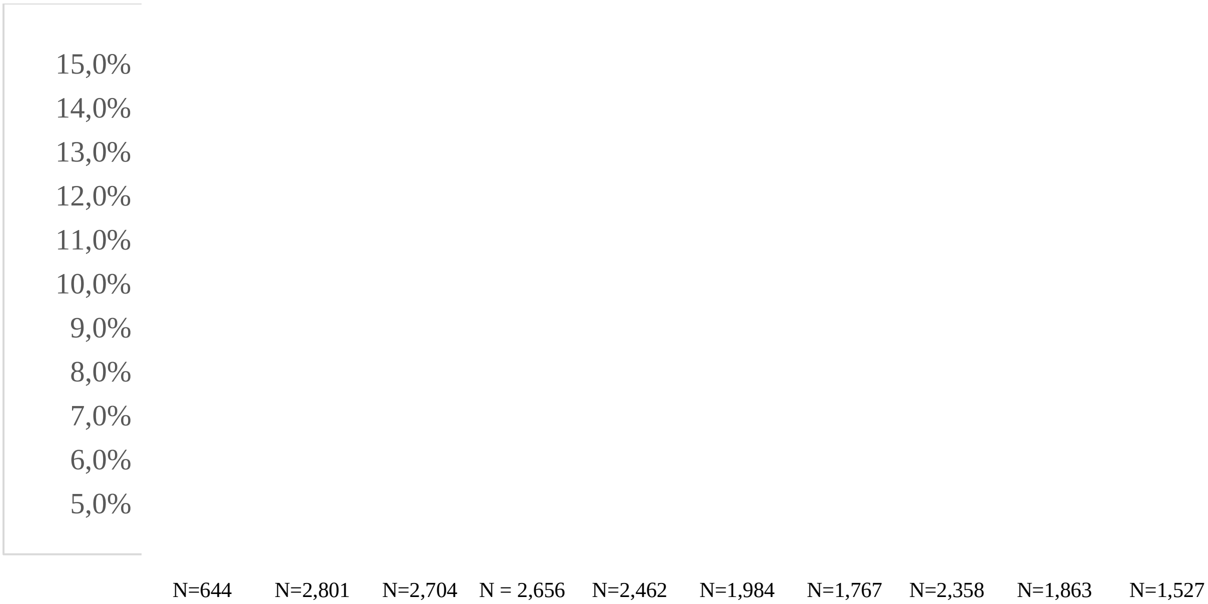
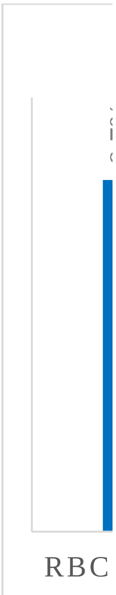

15,0%
14,0%
13,0%
12,0%
11,0%
10,0%
9,0%
8,0%
7,0%
6,0%
5,0%
N=644
N=2,801
N=2,704
N = 2,656
N=2,462
N=1,984
N=1,767
N=2,358
N=1,863
N=1,527

Figure 5

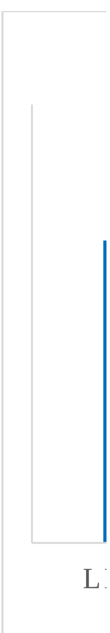
Herding Measures by Risk-Based Capital Ratios




N=1,510 N = 4,786 N = 1,454 N = 85

Figure 6

Herding Measures by Product Line Focus



N=460 N=2,306 N = 555 N = 4,077