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Correlated Trading by Life Insurers and Its Impact on Bond Prices

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Abstract

Our evidence indicates that U.S. life insurers' decisions to buy and sell individual corporate bonds are correlated across companies within the life insurance industry. On average, the correlation in sell decisions is greater in smaller bonds, bonds with lower ratings, bonds that have been downgraded, and bonds that have recently experienced relatively large abnormal returns. Correlated trading was also elevated during the financial crisis. In addition, correlated buying and selling are greater when insurers designated as systemically important financial institutions are actively trading. We also find that the bonds that insurers sell in a correlated manner exhibit negative average abnormal returns during the quarter in which insurers are selling. One explanation is that insurers' correlated selling is temporarily pushing bond prices below their fundamental value. In this case, we would expect prices to bounce back in the subsequent quarter. However, we do not find a rebound in prices and therefore our evidence supports the alternative explanation that insurers' correlated selling is impounding information into bond prices.

Introduction

Academics, insurance professionals, and regulators continue to debate whether traditional insurance activities of insurers are a source of systemic risk.[1] For example,

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[1]Many commentators acknowledge that nontraditional activities, such as trading credit default swaps, could cause insurance groups to be systemically important (see Harrington, 2009; Cummins and Weiss, 2014).

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 Metlife challenged the ruling, and in March 2016, a judge rescinded the SIFI designation.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 appealed the decision, but in January 2018, the government agreed not to pursue the case further (Schroeder, 2018).

One channel through which life insurers could contribute to systemic risk is via their correlated trading of corporate bonds.[2] As of 2016, life insurers held over $2.3 trillion in bonds, which represents about 26 percent of the value of all U.S. corporate bonds outstanding.[3] If insurers' trading of securities is correlated across insurers, then they could potentially disrupt financial markets by causing security prices to move temporarily away from fundamental values. Schwarcz and Schwarcz (2014) forcefully make this argument and call for greater regulation. The FSOC also refers to this mechanism when justifying its designation of Prudential as an SIFI (FSOC, 2013).[4]

On the other side of the spectrum from those who argue that life insurer correlated trading contributes to systemic risk, Vaughn (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 sales from other institutions, insurers maintain their positions and/or even step in on the buy side. A related point of view is that insurer investment decisions are unlikely to influence security prices because even though life insurers' asset portfolios are large, they are typically buy-and-hold investors. Paulson and Rosen (2016) report that the annual turnover rate of corporate bonds held by life insurers is about one-fifth of the turnover rate of corporate bonds in general. On the other hand, trading in corporate bonds is relatively thin, and so even a relatively small amount of trading can potentially impact prices. Also, recent evidence by Ellul, Jotikasthira, and Lundblad (2011, 2014) and Merrill, Nadauld, and Strahan (2014, 2017) is consistent with life insurer investment behavior temporarily impacting security prices.

The purpose of this article is to examine (1) the extent to which life insurers' investment decisions in corporate bonds are correlated with each other, (2) insurer characteristics that are associated with life insurer correlated trading, and (3) whether life insurer correlated trading in corporate bonds cause bond prices to move

[2]There are other arguments for how insurers could contribute to systemic risk, including concerns about an insolvency of 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 (Foley-Fisher, Narajabad, and Verani, 2015). Cummins and Weiss (2014) focus on whether reinsurance activities contribute to systemic risk. Also see Acharya, Biggs, and Richardson (2014), Billio et al. (2012), Chen et al. (2014); Manconi, Massa, and Yasuda (2012), Neale, et al. (2012), Weiss and Muhlnickel (2014), and Weiss, Bierth, and Irresberger (2015).

[3]See American Council of Life Insurers (2016) and the Securities Industry and Financial Markets Association (2018).

[4]Also, see Getmansky et al. (2016) and Koijen and Yogo (2016).

temporarily away from fundamental values. To measure correlated trading, we use the traditional measure introduced by Lakonishok, Shleifer, and Vishny (1992), hereafter referred to as the LSV measure, and a measure based on the volume of insurer buying versus selling introduced by Oehler and Chao (2000), hereafter referred to as the volume-based measure.

Both correlated buying and selling can potentially move prices temporarily away from fundamental values and thereby distort decisions. Nevertheless, correlated selling is sometimes emphasized because prices lower than fundamental values can impose losses on others holders of the affected securities, which in turn can cause liquidity problems and trigger or exacerbate fire sales, further impacting prices and possibly the financial system (see, e.g., Schwarcz and Schwarcz, 2014). While we examine both correlated buying and correlated selling, we emphasize the latter, as our evidence on the impact of correlated trading on prices indicates that correlated selling is associated with abnormal price changes prior to and during the quarter in which correlated selling occurs. We find less evidence that correlated buying is associated with abnormal price changes.

Given the concerns that have been raised about the potential for insurers' investment activity to disrupt financial markets, it is not surprising that other researchers have been addressing similar issues. Cai, Han, and Li (2012) and Cai et al. (2019) analyze the buying and selling of corporate bonds by mutual funds, pension funds, and both property–liability and life insurers. They find that there is correlation in bond trading within each type of institution but that the correlation in insurers' decisions is on average greater than that of mutual funds and pension funds. In contrast, we focus on life insurers and test hypotheses regarding life insurer characteristics that are associated with correlated trading.[5] For example, we find that risk-based capital (RBC) ratios and whether an insurer is part of a group that has been designated as an SIFI are related to insurer correlated trading. Importantly, Cai et al. (2019) find significant price reversals in the quarters following high correlated selling, but we do not. We explore possible explanations for the different findings at the end of this article.

Getmansky et al. (2016) use cosine similarity to examine the similarity of portfolios and trading at the asset class and issuer levels for pairs of 90 publicly traded insurers. They show that insurers with similar portfolios exhibit similar selling decisions, and this correlation is stronger among larger insurers. They also find that insurers with high portfolio similarity and low RBC ratios are more likely to sell the same types of assets. Thus, similar to this article, Getmansky et al. examine insurer and security characteristics that are related to correlated trading among insurers, using a different measure of correlation. In addition, they examine insurer investments in security classes other than corporate bonds, whereas we examine correlated trading in individual corporate bonds. They do not, however, examine the impact of correlated trading on security prices.[6]

[5]Given that life insurers have the largest holdings of corporate bonds (Global Macro Monitor, 2018), they are often identified as the industry that is most likely to disrupt financial markets because of correlated trading. See, for example, Schwarcz and Schwarcz (2014).

Our evidence indicates that life insurers exhibit correlated trading. The overall average LSV 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 and sell LSV measures, as proposed by Wermers (1999). The overall buy and sell LSV measures for individual corporate bonds have an average value of 11.1 and 9.4 percent, respectively, indicating that correlated trading by life insurers is not concentrated on one side of the market. The volume-based measures also indicate that on average life insurers exhibit correlated trading. 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.

Correlated selling is greater in lower rated bonds and recently downgraded bonds, which is consistent with RBC requirements increasing insurers' cost of holding bonds with greater credit risk. Moreover, correlated selling in downgraded bonds is greater among insurers with relatively high RBC ratios.[7] This is consistent with Ellul et al.'s (2015) evidence that insurers with low RBC ratios tend not to sell downgraded securities because the impact of realizing the loss on a downgraded security is greater than the extra capital required to hold the security. We also find that, holding other factors constant, correlated trading is on average greater in bonds in which SIFI insurers have a relatively high proportion of the trading volume.[8] Thus, a necessary condition for SIFI insurers to be systemically important through the correlated trading channel seems to be satisfied—correlated trading is greater when SIFI insurers trade more.

In addition, we find that insurer correlated trading occurs when such trading is more likely to be destabilizing to financial markets. More specifically, insurers' correlated selling is consistent with momentum trading, that is, insurers exhibit more correlated selling in bonds that experienced negative abnormal returns in the prior quarter. This behavior can exacerbate temporary price movements away from fundamental values (see Bank of England, 2014).

[6]Paulson and Rosen (2016) also provide evidence relevant to the debate on whether security trading by insurers contributes to or lessens systemic risk. They show that insurers tend to provide liquidity to the investment grade corporate bond market when bonds are less liquid than average, but they do not find that this behavior increased during the financial crisis.

[7]RBC is a tool used by the regulators to measure the solvency of an insurance company. It is the ratio of total adjusted capital (capital, surplus, and applicable valuation reserves) to risk-based capital. The ratio represents the amount of capital that an insurer has relative to a measure of the amount of capital that is "needed" given its business operations, size, and risk profile. The denominator of the ratio, RBC, is calculated based on a formula provided by the National Association of Insurance Commissioners (NAIC). Insurance companies with an RBC ratio below 2.0 are subject to supervisory interventions. For other studies using RBC ratios, see Ambrose, Cai, and Helwege (2008), Ellul, Jotikasthira, and Lundblad (2011, 2015), and Becker and Ivashina (2015).

[8]The FSOC designated three insurers (AIG, MetLife, and Prudential) as systemically important.

To examine whether insurer correlated trading temporarily impacts bond prices, we examine abnormal returns in the quarter during and the quarter subsequent to the insurers' correlated trading. The analysis produces evidence that portfolios with high sell correlated trading have abnormal returns that are significantly lower during the correlated trading period than the abnormal returns of portfolios of bonds with low sell correlated trading, especially when insurers that are part of a group that has been designated as a SIFI are involved in trading the bonds. However, we do not find that the returns rebound in the subsequent quarter, which is what one would expect if the correlated selling was temporarily distorting prices. Thus, the evidence is more consistent with insurer correlated selling helping to impound information into prices.

The article proceeds as follows. In the next section, we develop hypotheses about how correlated trading is likely to vary across insurers. We describe the correlated trading measures in the third section and the data in the fourth section. We present evidence on how correlated trading varies with insurer characteristics in the fifth section. The sixth section contains the analysis of portfolio returns around correlated trading. We end with a summary of the evidence and a brief discussion of the implications for issues related to the systemic risk of life insurers.

Hypotheses

Determinants of Correlated Trading

Drawing on the general literature that examines why institutional investors' securities transactions might be correlated, we develop hypotheses regarding the characteristics of life insurers that are likely to be associated with correlated trading and the economic conditions (time periods) when insurers would be more likely to exhibit correlated trading.[9]

One explanation for correlated trading among a group of firms in the same industry is that each firm is affected in similar ways by economic information and therefore they tend to respond to economic information in the same manner (Froot, Scharfstein, and Stein, 1992).[10] The 2008–2009 financial crisis was a time period with a number of major information events relevant to the management and valuation of life insurers. For example, equity values dropped, Treasury rates declined, and credit spreads increased. These changes, along with higher overall uncertainty, could cause life insurers to rebalance their portfolios in a

[9]We only discuss hypotheses that are either specific to insurers or that relate to the systemic risk of insurers. The Online Appendix (Chiang and Niehaus, 2019) discusses other hypotheses. For example, the information cascade theory (Bikhchandani, Hirshleifer, and Welch, 1992) implies that correlated trading is greater in smaller bonds and less liquid bonds, all else equal. Therefore, the empirical analysis includes variables related to bond size and bond liquidity.

[10]Ellul et al. (2018) provide a model in which the shared business model of annuity providers induce insurers to hold similar illiquid, risky, bond portfolios, which are sold at the same time in a market downturn. Also, see Chaderina, Murmann, and Scheuch (2018), who show how correlated selling can occur because institutions do not take into account the negative externality of their trading on one another.

similar manner in an effort to change their risk exposures and/or to take advantage of mispricing opportunities. Correlated trading is also more likely to be a concern during time periods in which the financial markets are disrupted in terms of falling prices and reduced liquidity. Therefore, we examine the following hypothesis:

H1: (Financial Crisis Hypothesis) Insurer correlated trading is greater during the financial crisis, all else equal.

Three insurance groups (each consisting of multiple life insurance companies) have been designated by the FSOC as SIFIs. As discussed in the Introduction, there is debate as to whether these institutions actually contribute to systemic risk. One channel through which they could be systemically important is correlated trading. Therefore, we examine whether correlated trading is greater when one or more of these three institutions are trading.

H2: (SIFI Hypothesis) Insurer correlated trading is greater when insurers that are part of a group that was designated as an SIFI are trading, all else equal.

Insurers have higher RBC requirements if they hold lower rated bonds. Therefore, a rating downgrade could induce correlated selling. On the other hand, selling a downgraded bond can force an insurer to recognize the loss on the bond and thereby reduce its reported capital (the numerator of the RBC ratio), which may deter insurers from selling downgraded bonds. Ellul et al. (2015) hypothesize that the latter effect is more important for insurers with low RBC ratios and they present evidence that insurers with higher RBC ratios are more likely to sell downgraded securities than insurers with low RBC ratios. We therefore examine the following two hypotheses:

H3: (Bond Rating Downgrade Hypothesis) Insurer correlated selling is greater in bonds that have been downgraded, all else equal.

H4: (Downgrade and RBC Hypothesis) Insurer correlated selling is higher in downgraded bonds among insurers with relatively high RBC ratios, all else equal.

One of the motivations for examining correlated trading among insurers is the concern that it could potentially disrupt financial markets by pushing prices away from fundamental values temporarily. Correlated trading is more likely to be disruptive if it is consistent with momentum trading, sometimes called procyclical trading (Bank of England, 2014), that is, if correlated selling (buying) follows price declines (increases). As a consequence, we examine the following hypothesis:

H5: (Momentum Trading Hypothesis) Insurer correlated selling (buying) is greater in bonds that have experienced abnormal prices declines (increases) in the prior quarter, all else equal.

Price Impact of Correlated Trading

We also examine abnormal price changes during the quarter in which correlated trading takes place and in the subsequent quarter.[11] If insurers' correlated trading temporarily pushes prices away from fundamental values, we would expect to observe negative (positive) abnormal returns during quarters in which correlated selling (buying) occurs and then a reversal in abnormal returns subsequently, as prices move back to their fundamental values.

H6: (Price Reversal Hypothesis). There are negative (positive) abnormal returns during the quarter in which sell (buy) correlated trading occurs followed by positive (negative) abnormal returns in the subsequent quarter.

MEASURING CORRELATED TRADING

LSV Measures

We begin by describing the traditional correlated trading measure that was originally proposed by Lakonishok, Shleifer, and Vishny (1992). In the following description, the referenced investor group is the entire group of insurers in our sample that transacted in bond i during quarter t. The proportion of the investor group that are net buyers of security i is called the buy ratio for security i during period t. It is denoted as $p_{i,t}$ and defined as $p_{i,t} = B_{i,t}/(B_{i,t} + S_{i,t})$, where

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

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

The idea is to test whether the insurers' buy ratio for security i differs from 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, p_t, for all corporate bonds, where

$$p_t = \frac{\Sigma_i B_{i,t}}{\Sigma_i B_{i,t} + \Sigma_i S_{i,t}}$$

The absolute difference, $| p_{i,t} - p_t |$, indicates whether the proportion of net buyers of bond i differs from the proportion of net buyers of all corporate bonds.[12]

[11] A number of papers have examined abnormal returns before, during, and after correlated trading in equities takes place. Although there is some variation across the studies, Grinblatt, Titman, and Wermers (1995), Wermers (1999), and Nofsinger and Sias (1999) find positive (negative) stock returns before during, and after institutional correlated buy (sell) trading. Sias (2004) finds that correlated trading is not positively associated with prior-period returns once he controls for prior-period correlated trading. Dasgupta, Prat, and Verardo (2011) also show that persistent correlated trading is negatively correlated with long-horizon returns. Gutierrez and Kelley (2009) document similar results.

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 LSV correlated trading measure for security i during period t with an expected value of zero:

$$LSV_{i,t} = \left|p_{i,t} - p_t\right| - AF_{i,t}, \qquad \text{where} \quad AF_{i,t} = \Sigma_{j=0}^{N_{i,t}} \left| \frac{j}{N_{i,t}} - p_t \right| \binom{N_{i,t}}{j} p_t^j (1 - p_t)^{N_{i,t}-j}$$

and $N_{i,t}$ is the number of insurers transacting in security i during period t. As $N_{i,t}$ increases, the adjustment factor declines. For example, if $p_t = 0.5$ and $N_{i,t}$ equals 3, the adjustment factor is 0.25, but if $N_{i,t}$ equals 25, the adjustment factor is 0.0806. The Online Appendix (Section 3.1) provides an example to illustrate the calculation of the adjustment factor.

Intuitively, a positive value for the LSV 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.

Wermers (1999) introduces separate buy and sell correlated trading measures, which we denote by LSV_B and LSV_S, by conditioning on whether the security had a higher (lower) buy ratio than the average buy ratio. That is,

$LSV\_B_{it} = LSV_{it}$ if $p_{i,t} > p_t$ and undefined otherwise,

$LSV\_S_{it} = LSV_{it}$ if $p_{i,t} > p_t$ and undefined otherwise.

The Online Appendix (Chiang and Niehaus, 2019) contains an example to illustrate the calculations underlying the LSV measures.

Incorporating Information on the Size of Trades

The LSV measures take into account the number of traders that are on one side of the market, but not the size of the trades. Thus, $50,000 of net buying by one institution is treated the same as $10 million of net buying by another institution. However, one might argue that the volume of trade (as opposed to the number of traders) on one side of the market would be a better predictor of price pressure effects of trading, all else equal. As a consequence, we utilize a measure used by Oehler and Chao (2000), which takes into account the volume of buy trades and sell trades by insurers. The volume-based measure for bond i in quarter t equals the absolute value of the difference between the amount purchased by insurers and the

[12]To illustrate, suppose that there are two bonds and three insurers. Also, assume that two of the insurers are net buyers of bond 1 so that $B_{1,t} = 2$, $S_{1,t} = 1$ and that one of the insurers is a net buyer of bond 2 so that $\#B_{2,t} = 1$, $\#S_{2,t} = 2$. Then $p_{1,t} = 2/3$, $p_{2,t} = 1/3$, and $p_t = 3/6$.

amount sold by insurers as a proportion of the total amount transacted by insurers:

$$\mathrm{VOL}_{it} = |\mathrm{Amt\ Purchased}_{it} - \mathrm{Amt\ Sold}_{it}|/[\mathrm{Amt\ Purchased}_{it} + \mathrm{Amt\ Sold}_{it}].$$

This measure is similar to the order imbalance measures used in a number of equity market studies (see, e.g., Chordia, Roll, and Subrahmanyam, 2002). Analogous to the buy and sell LSV measures, we also calculate separate buy and sell measures based on volume and denote them by VOL_B and VOL_S, respectively. VOL_B (VOL_S) is the value of the VOL if buy volume of insurers is greater (less) than sell volume by insurers, and undefined otherwise.

In addition to taking into account the amount transacted, the volume-based measures differ from the LSV measures in that they do not subtract a benchmark measure of insurer buy versus sell volume in the bond market. Stated differently, the volume-based measures do not control for the overall movement of insurers in or out of bonds. Instead, the volume measures capture differences in buy and sell volume for a particular bond independent of insurers' transactions in other bonds.

DATA

The Online Appendix (Chiang and Niehaus, 2019) describes the sample selection process in detail. Here we briefly identify the data sources. We obtain insurer transactions in individual bonds over quarterly time periods starting in the first quarter of 2003 and ending in the fourth quarter of 2011 from Schedule D, Parts 3, 4, and 5 of insurers' annual statements. The transaction data are merged with the Fixed Income Securities Database (FISD), which provides bond characteristics. We restrict our sample of bonds by applying criteria similar to Cai, Han, and Li (2012); see the Online Appendix for more details. The data are then merged with the Trade Reporting and Compliance Engine (TRACE) enhanced data to obtain liquidity, volume, and return measures. We follow Bessembinder et al. (2009) and Dick-Nielsen (2014) to clean the TRACE data (see the Online Appendix). These data are merged with insurer annual statement data to obtain insurer characteristics, such as size, capitalization, and product focus. Our final sample consists of 176,541 bond transactions in 5,752 bonds by 904 life insurers. The empirical analysis is conducted at the bond-quarter level; there are 20,760 such observations.

In Table 1, 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 have 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 1 and 10, where 1 indicates the lowest rating (in default) and 10 indicates the highest rating (AAA).[13] The Credit Rating variable used in our analysis is the average rating of the three major credit rating agencies. For example, if a bond's numerical scores from

[13]The numerical score has the following correspondence to the letter ratings: AAA = 1, [AA, AAA) = 9, [A,AA) = 8, [BBB,A) = 7, [BB,BBB) = 6, [B,BB) = 5, [CCC,B) = 4, [CC,CCC) = 3, [C, CC) = 2, default = 1.

Table 1
Characteristics of Bonds and Insurers in the Sample

	Var Name	Mean	Median	Min	Max	Stdev
Bond characteristics						
Maturity when issued (yrs.)		13.9	10.0	2.0	100.0	9.1
Bond age (yrs)	Bond_Age	4.1	3.3	1.0	24.3	2.7
Face amount ($mill)	Bond_Size	860.3	551.5	0.1	7,362.8	830.7
Credit rating	Rating	6.9	7.0	1.0	10.0	1.2
Investment grade (%)	InvGr	67.8	100.0	0.0	100.0	46.7
Upgraded (in %)	UpGr	2.7	0.0	0.0	100.0	16.3
Downgraded (in %)	DownGr	7.2	0.0	0.0	100.0	25.9
Prior qtr abn return (in %)	PrRet	−0.4	−0.2	−24.7	21.3	5.5
Amihud liq measure	Liquidity	0.7	0.4	0	5.0	0.8
Insurer characteristics						
# of insurers transacting	#InsTrans	7.8	7.0	5	72	3.8
% of volume by SIFIs	SIFI_Vol	21.3	2.9	0.0	1.0	29.2
Avg risk-based capital ratio	Avg RBC	8.4	8.1	5.2	20.0	2.2
Avg return on assets (in %)	Avg ROA	0.9	0.9	−33.3	28.0	2.1
Avg value of assets ($billions)		43.8	32.3	0.1	237.0	37.5
Avg 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

Note: Maturity is the number of years until the bond matures. Bond age is the number of years that the bond has existed. Bond_Size is the face amount of the bond ($millions). Credit rating is the average of the S&P, Moody's, and Fitch ratings and takes a value between 1 and 10, with 10 being AAA, 9 above AA, etc. Investment grade is equal to one if the bond is investment grade (Rating ≥ 7) and zero otherwise. Amihud liquidity is the measure of liquidity in Amihud (2002) winsorized at the 1 and 99 percentile values. Prior quarter abnormal return is the abnormal return in the previous quarter winsorized at the 1 and 99 percentile values. SIFI_Vol is the proportion of insurer volume in the bond from companies that are part of a group that has been designated as an SIFI. The insurer characteristics are for the prior year and are volume-weighted averages of the variable for the insurers transacting in the bond in the quarter. #InsTrans is the number of insurers transacting in the bond during the quarter,RBC is the risk-based capital ratio, winsorized at the 1 and 99 percentile values. Assets is total assets ($billions). 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.

the three rating agencies equal 9, 9, and 8, then our Credit Rating variable takes a value of 8.67 (26/3). The average (median) value of Credit Rating in our sample is 6.9 (7.0) and 67.8 percent of the bonds transacted have an average credit rating of 7 or above, which is designated as an investment grade rating. The percentage of the bond-quarter observations in the sample that have a rating upgrade during the quarter is 2.7 percent and the percentage that have a downgrade in the quarter is 7.2 percent, which yields a downgrade-to-upgrade ratio equal to 2.7.[14]

The average (median) number of insurers transacting (#InsTrans) is 7.8 (7.0), which means that in a given quarter, there are on average 7.8 insurers buying or selling a given bond. The average proportion of insurer volume from insurers that are part of a group that has been designated as an SIFI (SIFI_Vol) is 21.3 percent. The median is only 2.9 percent, indicating a highly skewed distribution. Thus, for some bonds and some quarters, SIFI insurer volume makes up a large proportion of the total insurer volume (100 percent in 277 of the 20,760 bond-quarter observations), but generally, SIFI insurer volume makes up a relatively small proportion of total insurer volume.

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.[15] Our approach to calculating the abnormal return is similar to Bessembinder et al. (2009). More specifically, 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 described above and either three or four maturity categories depending on whether the bond is investment grade or not. For investment-grade bonds (Rating ≥ 7), 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 (Rating $=$ 1 to 6), the categories are 1 to 7 years, 7 to 10 years, and 10 or more years. This yields 34 benchmark portfolios.[16] Abnormal returns equal the return on the bond in the quarter minus the return on the corresponding benchmark portfolio. If a bond's rating category changes during a quarter, then we change the benchmark portfolio to be a weighted average of the benchmark corresponding to the different rating categories. The average winsorized abnormal return (at the 1 and 99 percent levels) during the quarter prior to the quarter in which we measure insurers' correlated trading is -0.4 percent.

To measure the characteristics of the insurers transacting in the bonds, 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

[14]In comparison, Standard & Poor's reports that the annual average downgrade-to-upgrade ratio from 2003 to 2011 (our sample period) for corporate bonds in general is 1.4, with the low being 0.7 in 2007 and the high being 4.0 in 2009 (see Standard & Poor's, 2012). Potential explanations for the higher ratio for our sample are that insurers hold a disproportionate number of higher rated bonds, downgrades are more likely for higher rated bonds, and insurers are more likely to trade downgraded bonds.

[15]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 $P_{i,T\text{-}x}$ is the bond price on day T-x (x days before the start of the quarter), $\mathrm{AI}_{i,T\text{-}x}$ is accrued interest on day T-x, and C is the coupon payment(s) received. $I_{i,T\text{-}x}$ is the matching portfolio value x days before the start of the quarter.

[16]Bessembinder et al. (2009) use 17 categories. Similar to us, they have four investment-grade categories, but they do not consider bonds rated below B, which gives them two non-investment-grade categories. In addition, they use three maturity categories for bonds rated from B to AA and two maturity categories for bonds rated AAA, yielding 17 categories in total.

that insurer. The insurer financial characteristics are measured as of the prior year end. The average (median) winsorized RBC ratio 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. 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.

Correlated Trading by Insurers

The first row of Table 2 reports that the average LSV measure (LSV) equals 10.2 percent, which indicates that on average the proportion of life insurers that are net buyers of a bond in a given quarter differs by 10.2 percent from what one would expect if insurers' buy versus sell decisions were independent draws from a binomial distribution with probability equal to the overall buy ratio of insurers during each quarter. Intuitively, life insurers have about a 10 percent higher probability of being on the same side of the market in individual bonds than would be expected if their decisions were independent.

The average LSV buy measure (LSV_B) for the sample is 11.1 percent and the average LSV sell measure (LSV_S) for the overall sample is 9.4 percent. These numbers indicate that among the bonds that have a higher (lower) insurer buy ratio than the overall insurer buy ratio during the quarter, insurers are on average 11.1 (9.4) percent more likely to buy (sell) than sell (buy). The comparable magnitude of the buy and sell measures indicates that the correlated trading of life insurers is not concentrated on the buy or sell side of the market.[17]

Also reported in row 1 of Table 2 are the volume-based correlated trading measures. On average, the overall volume measure (VOL) is 60.5 percent, indicating that on average insurers are typically on one side of the market in individual bonds. The average buy volume measure is 56.5 percent, which indicates that when insurers' buy volume exceeds sell volume, the average buy volume is 3.6 times the sell volume.[18] The average sell measure based on volume is 63.7 percent, which indicates that when insurers' sell volume exceeds buy volume, the average sell volume is 4.5 times the buy volume. Thus, both the buy and sell measures are statistically and economically significant.[19] The correlation coefficient between the overall trading measures, LSV

[17]All of the reported means for the LSV measures are statistically different from zero using a t-test. If all of the bonds in the initial sample with five transactions are used to calculate the correlated trading measures (98,906), as opposed to those that went through the various data screens outlined in Table A1 (see Online Appendix), the mean measures are higher: LSV = 14.4 percent, LSV_B = 11.1 percent, and LSV_S = 17.5 percent. If we require only three transactions each quarter instead of five transactions, then the mean measures are lower.

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

[19]The Online Appendix (Chiang and Niehaus, 2019) provides the underlying assumptions used to test the statistical significance of the volume based measures.

TABLE 2
Mean Values of Correlated Trading Measures for Various Subsamples

		LSV Measures			Volume Measures		
	N	Overall (%)	Buy (%)	Sell (%)	Overall (%)	Buy (%)	Sell (%)
Whole sample	20,760	10.2	11.1	9.4	60.5	56.5	63.7
Time period							
2002–2007	13,576	9.4	10.0	8.8	58.3	54.7	61.3
2008–2009	4,117	**13.0**	**15.3**	**10.9**	**67.5**	**62.6**	**70.5**
2010–2011	3,067	**10.3**	**10.7**	9.8	**60.9**	**57.3**	**64.1**
SIFI volume							
SIFI_Vol < mean	13,358	9.9	10.9	9.0	60.7	57.6	63.5
SIFI_Vol > mean	7402	**10.8**	11.5	**10.1**	60.3	55.3	64.0
Rating							
InvGr = 0	6,689	14.9	15.1	14.8	69.5	63.8	72.7
InvGr = 1	14,071	**8.0**	**9.6**	**6.2**	**56.3**	**53.7**	**58.6**
Rating change							
DownGr = 1	1,483	13.9	7.4	15.7	70.1	47.6	74.9
No change	18,709	**9.9**	**11.1**	**8.6**	**59.6**	**56.6**	**62.2**
UpGr = 1	568	**11.9**	**14.0**	9.6	**66.1**	**62.4**	**70.1**
Downgraded bonds & insurers' RBC ratio							
AvgRBC < 7	298	14.6	9.0	16.3	68.1	51.2	72.6
7 ≤ AvgRBC < 9	799	13.5	6.7	15.4	69.4	42.3	74.4
AvgRBC ≥ 9	386	13.9	7.3	15.8	73.2	54.0	77.6
Bond size							
< $200m	1,9314	15.8	15.5	16.1	67.6	60.3	72.9
[$200m,$1500m)	16,031	**10.1**	**11.2**	**9.0**	**60.4**	57.0	**63.1**
[$1500m,$3000m)	2,267	**7.3**	**8.1**	**6.6**	**56.5**	**51.0**	**60.6**
> $3000m	531	6.6	5.7	7.4	55.3	48.0	59.2
Liquidity							
1st quintile	3,444	11.5	12.6	10.4	61.7	58.8	64.0
2nd quintile	7,119	**10.0**	11.6	**8.4**	**60.0**	57.0	62.4
3rd quintile	6,143	9.6	10.6	8.7	60.3	56.1	63.3
4th quintile	3,079	9.7	10.5	9.0	60.7	**53.7**	**65.9**
5th quintile	975	10.6	10.2	**11.0**	61.6	55.2	67.3
Pr Qtr Abn Ret							
Pr_Ret < −1%	7,527	11.5	11.8	11.1	62.2	57.9	65.6
−1% < Pr_Ret < 1%	7,342	**8.6**	**9.7**	**7.6**	**58.6**	**54.6**	**61.6**
Pr_Ret > 1%	5,891	**10.7**	**11.8**	**9.6**	**60.8**	57.0	**63.8**

Note: N = total number of observations used in the overall measure; this number is the sum of the number of observations used in the buy and sell measures. Bold indicates that the mean value differs from the mean value in the row above at the 0.05 level based on a two-tailed t-test. See Table 1 for variable definitions. The mean of SIFI_Vol is 21.3 percent.

and VOL, is 0.54, which suggests that the two measures are related but also capture different information.

Insurer Correlated Trading Measures Over Time

Figure 1 in the Online Appendix (Chiang and Niehaus, 2019) illustrates that both the average LSV and VOL measures increase gradually from 2004 through 2009. After reaching a peak in 2009, the average measures decrease in 2010 and 2011. In Table 2, we report the average correlated trading measures for the period prior to, during, and after the 2008–2009 financial crisis. We use a difference in means test to determine whether the value reported in one row is different from the value in the row above it. When the reported mean value is in bold font, then it differs from the value above at the 0.01 level. For example, the average overall LSV measure in 2008–2009 (13.0 percent) is significantly greater than the mean value in 2003–2007 (9.4 percent) and greater than the mean value in 2010–2011 (10.3 percent). Consistent with the Financial Crisis Hypothesis (H1), we find that each of the correlated trading measures are greater during the financial crisis compared to the prior and subsequent periods. The higher insurer correlated trading measures during a period of market turmoil lends support to the argument that policymakers should be concerned about insurer correlated trading.

Do Correlated Trading Measures Vary With Insurer and Bond Characteristics?

To provide preliminary evidence on Hypotheses 2–5, we also report in Table 2 the mean values for the correlated trading measures for various subsets of bond-quarter observations. Again, bolded values indicate statistical significance relative to the value above. Rather than discuss each panel, we simply list the main results here. The Online Appendix (Chiang and Niehaus, 2019) includes a fuller discussion.

- LSV measures are greater when SIFIs have a high proportion (greater than mean) of trading volume
- Investment-grade bonds have lower LSV and VOL measures
- Downgraded bonds have higher overall LSV and VOL measures, higher sell LSV and VOL measures, but lower buy LSV and VOL measures
- The RBC ratio is not significantly related to the LSV or VOL measures for downgraded bonds
- Smaller bonds (AmtOutst) have higher LSV and VOL measures
- No pattern is detected between bond liquidity and LSV and VOL measures
- LSV and VOL measures are higher when the prior-quarter abnormal returns are less than -1 percent or greater than 1 percent

Panel Regressions of Correlated Trading Measures

To examine Hypotheses 2–5 in a multivariate setting, we report in Table 3 the results of six panel regressions corresponding to each of the correlated trading measures. We include the following variables: Bond_Age, SIFI_Vol, UpGr, DownGr, and Liquidity, which are defined in Table 3. In addition, we use variants of other variables

TABLE 3
Panel Regressions for Correlated Trading Measures

	LSV	VOL	LSV_B	VOL_B	LSV_S	VOL_S
Bond_Age	−0.034	0.072	−0.063	−0.118	0.014	0.271***
	(0.025)	(0.054)	(0.043)	(0.096)	(0.035)	(0.074)
Log_Bond_Size	−0.045***	−0.096***	0.016	−0.016	−0.043***	−0.086***
	(0.007)	(0.013)	(0.023)	(0.062)	(0.007)	(0.012)
Liquidity	0.001	−0.003	−0.004	−0.014*	0.005*	0.004
	(0.002)	(0.004)	(0.004)	(0.008)	(0.003)	(0.006)
Rating1	−0.037***	−0.063***	−0.027**	−0.027	−0.032***	−0.046***
	(0.003)	(0.007)	(0.011)	(0.022)	(0.004)	(0.007)
Rating2	−0.020***	−0.046***	−0.008	−0.069**	−0.012	−0.038**
	(0.006)	(0.014)	(0.012)	(0.027)	(0.009)	(0.018)
PrRet_LT0	−0.015	−0.184**	−0.021	0.229	−0.132***	−0.426***
	(0.042)	(0.083)	(0.089)	(0.179)	(0.049)	(0.105)
PrRet_GT0	−0.053	0.089	−0.121	−0.374*	0.121**	0.358***
	(0.047)	(0.097)	(0.092)	(0.198)	(0.060)	(0.127)
SIFI_Vol	0.019***	0.047***	0.038***	0.052***	0.013*	0.038***
	(0.005)	(0.011)	(0.008)	(0.019)	(0.007)	(0.015)
Avg RBC_LT7	0.017***	0.031***	0.018***	0.026*	0.014**	0.030**
	(0.004)	(0.008)	(0.007)	(0.014)	(0.006)	(0.012)
AvgRBC_BT7&9	0.008**	0.012*	0.004	0.008	0.011**	0.017*
	(0.003)	(0.007)	(0.006)	(0.012)	(0.005)	(0.010)
UpGr	0.006	0.044***	0.016	0.070***	−0.010	0.030
	(0.008)	(0.015)	(0.012)	(0.025)	(0.010)	(0.021)
DownGr	0.024**	0.089***	−0.021	0.049	0.055***	0.087***
	(0.010)	(0.020)	(0.027)	(0.062)	(0.011)	(0.022)
Avg RBC_LT7	−0.029**	−0.071***	−0.042	−0.144*	−0.035**	−0.036
× DownGr	(0.013)	(0.027)	(0.033)	(0.075)	(0.015)	(0.031)
AvgRBC_BT7&9	−0.020*	−0.050**	−0.009	−0.114	−0.038***	−0.054**
× DownGr	(0.012)	(0.024)	(0.030)	(0.076)	(0.013)	(0.027)
#InsTrans	0.044***	−0.109***	0.038***	−0.143***	0.053***	−0.094***
	(0.004)	(0.008)	(0.006)	(0.013)	(0.005)	(0.010)
AvgROA	−0.089	−0.165	−0.197	−0.603**	0.078	−0.002
	(0.078)	(0.156)	(0.128)	(0.274)	(0.108)	(0.208)
AvgLogAssets	−0.007***	0.012***	−0.013***	−0.002	−0.001	0.022***
	(0.001)	(0.003)	(0.002)	(0.005)	(0.002)	(0.004)
Avg Life_Foc	−0.000	0.025	0.004	0.056**	0.001	0.029
	(0.007)	(0.016)	(0.012)	(0.027)	(0.011)	(0.021)
Avg Ann_Foc	0.001	0.038***	−0.008	0.053***	0.008	0.033**
	(0.005)	(0.011)	(0.008)	(0.018)	(0.007)	(0.014)
Avg AH_Foc	0.013	0.012	0.018	0.007	0.013	0.012
	(0.010)	(0.022)	(0.016)	(0.038)	(0.015)	(0.029)
R^2	0.29	0.30	0.36	0.37	0.41	0.40
N	18,628	18,628	8,256	7,109	8,425	9,602

Note: The dependent variable is one of the six correlated trading measures for bond i during quarter t. The explanatory variables include the following insurer characteristics. #InsTrans = the natural logarithm of the number of insurers transacting in the bond during the quarter; SIFI_Vol = 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; 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. The explanatory variables include the following characteristics of bond i during quarter t: Bond_Age = age in years. Log_Bond_Size = logarithm of average amount outstanding. Rating1 is the first segment of a linear spline of Rating and Rating2 is the second segment, where Rating = average rating score (1 = default, 10 = =AAA). The knot for the spline is at 7, the threshold for an investment-grade rating. UpGr = 1 if the 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_LT0 is the first segment of a linear spline for the previous quarter's winsorized abnormal return for the bond and PrRet_GT0 is the second segment of the spline, where the knot for the spline is equal zero. 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.

previously introduced. We include the natural logarithm of the bond size (Log_Bond_Size). We use a linear spline of the variable Rating, where the knot in the spline is at the investment grade cutoff, a value of 7. This allows the rating sensitivity of the correlated trading measures to vary based on whether the bond is investment grade or not. We also use a linear spline to examine the impact of prior abnormal returns (PrRet) on correlated trading. The knot in the spline is at zero, which yields two variables in the regression: PrRet_LT0 and PrRet_GT0. This specification allows the relationship between correlated trading and prior abnormal returns to differ when abnormal returns are negative versus positive.

The Downgrade and RBC Hypothesis (H4) implies that correlated selling of downgraded bonds is greater for insurers with relatively high RBC ratios. To examine this hypotheses, we include interaction variables between the dichotomous variable indicating that the bond was recently downgraded (DownGr) and two dichotomous variables indicating whether the average RBC ratio of the insurers trading the bond is less than 7 (RBC_LT7) or between 7 and 9 (RBC_BT7&9). RBC ratios of 7 and 9 roughly correspond to the 25th and 75th percentile values of the RBC ratio across the sample.

We also include control variables for the average size, profitability, and product focus of the insurers trading the bond during the quarter. These variables are the natural logarithm of the weighted average of the insurers' assets, the weighted average of the insurers' return on assets, and the weighted average of dichotomous variables indicating whether the insurer has 75 percent or more of its business in either life, annuities, or accident and health insurance. We also control for the number of insurers transacting in the bond during the quarter. Finally, we include bond and quarter fixed effects to control for time-invariant unobservable bond characteristics and time effects that may affect correlated trading.

To conserve space, we report but do not discuss the coefficients on the control variables. Instead, we focus on the variables related to Hypotheses 2–5. Consistent with the SIFI Hypothesis (H2), the coefficient on SIFI_Vol is positive and statistically significant in each of the regressions, indicating that correlated trading increases with the relative trading volume of insurers that are part of a group that was designated as an SIFI, all else equal. This finding lends support to the argument that the insurers designated as SIFIs potentially contribute to systemic risk through the correlated trading channel.

The negative coefficients on the two Rating variables indicate that as the bond's rating declines, correlated trading increases, on average. For the volume regressions, we cannot reject that the coefficient on the two rating variables are equal. However, for the overall LSV and sell LSV regressions, the coefficient on the below-investment-grade rating variable (Rating1) is significantly greater in magnitude than the coefficient on the investment-grade rating variable (Rating2), indicating that the negative relation between ratings and correlated selling is greater for non-investment-grade bonds.

The positive coefficients on DownGr in the overall and sell models indicate that correlated selling of downgraded bonds is higher when insurers with relatively high

RBC ratios (greater than 9) trade the bond (the omitted group for the interaction variables). The negative coefficients on the interaction variables indicates that correlated selling of downgraded bonds is lower when insurers with lower RBC ratios trade the bonds.[20] These findings are consistent with the Downgrade and RBC Hypothesis (H4) and the literature that indicates that insurers with relatively lower RBC ratios tend not to sell downgraded bonds (Ellul et al., 2015).

We do not find that the coefficients on the prior abnormal return variables are statistically significant in the correlated buy trading regressions. However, for correlated sell trading, we find a negative coefficient when abnormal returns are negative (PrRet_LT0) and a positive coefficient when returns are positive (PrRet_GT0). This indicates greater correlated selling as prior abnormal returns increase, in both the negative and positive direction.[21] The greater correlated selling following greater negative abnormal returns is consistent with the Momentum Trading Hypothesis (H5).[22]

INSURER CORRELATED TRADING AND BOND ABNORMAL RETURNS

Methodology

We now examine whether life insurer correlated trading is associated with abnormal returns using a methodology similar to that employed by Barber, Odean, and Zhu (2009a,2009b) and Dorn, Huberman, and Sengmueller (2008) in their studies of equity market correlated trading. Cai et al. (2019) use a similar approach. We place bonds in portfolios based on their buy and sell correlated trading measures and we conduct separate analyses for the portfolios formed using LSV measures and the portfolios formed using the volume-based measures. For each quarter, we divide all of the bonds in the sample in two categories: (1) those with a nonmissing buy measure and (2) those with a nonmissing sell measure. The bonds in the first category are then divided into quintiles based on the magnitude of their buy measures. Portfolio LSV_B1 (VOL_B1) consists of the bonds with the lowest buy measures in each quarter using the LSV (volume-based) buy measure. Portfolio LSV_B5 and VOL_B5 consists of the bonds with the highest buy measures. We repeat the same ranking procedure for bonds with nonmissing sell measures, creating portfolios LSV_S1 (VOL_S1) to LSV_S5 (VOL_S5), where portfolio LSV_S1 (VOL_S1) consists of the bonds with lowest LSV (volume-based) sell measures in each quarter and LSV_S5 (VOL_S5)

[20]The sum of the coefficients on the Downgr and the interaction variables gives the effect on correlated trading of downgraded bonds when insurers with lower RBC ratios trade the bond. Although the interaction coefficients are negative in the sell regressions, the sum of the coefficients on Downgr and the interaction variables is positive and statistically different from zero, consistent with greater correlated selling overall for downgraded bonds, supporting the Downgrade Hypothesis (H3).

[21]We also replaced the spline for abnormal returns with the absolute value of prior abnormal returns. The coefficient on the absolute value variable is positive and significant at the 1 percent level.

[22]The Online Appendix (Chiang and Niehaus, 2019) describes several robustness checks and extensions to the regression analysis.

consists of the bonds with the highest LSV (volume-based) sell measures in each quarter.

Table 4 provides information about the portfolios formed using the LSV measures and Table 5 provides information about the portfolios formed using the volume-based measures. The second and third columns of each table provide descriptive information about the average number of bonds and the average correlated trading measure in the portfolio over the sample period.[23] Focusing first on Table 4, the average LSV buy measure in portfolio LSV_B5 is 36.2 percent and the average LSV sell measure in portfolio LSV_S5 is 29.8 percent, both of which suggest a substantial degree of correlated trading in the bonds in these portfolios. Portfolios LSV_B4 and LSV_S4 have average measures of 20.9 percent and 20.7 percent, respectively, also indicating a high degree of correlated trading in the bonds in these portfolios. In contrast, portfolios LSV_B1 and LSV_S1 have LSV measures that are negative, indicating little correlated trading in the bonds in these portfolios. Similarly, Table 5 indicates that VOL_B5 and VOL_B4 have high average buy measures based on volume and VOL_S5 and VOL_S4 have high average sell measures based on volume, whereas VOL_B1 and VOL_S1 have low volume-based measures.

The last three columns of Tables 4 and 5 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. As described earlier in the Data section, we calculate abnormal returns using the return on a matching portfolio based on maturity and credit ratings.[24] For each of the 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.[25] This is repeated for each bond in the 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, Guan, and Yang, 2015).[26]

[23]The average number of bonds in the various portfolios can vary because the number of bonds with nonmissing buy and sell measures varies by quarter.

[24]We discuss alternative methods of calculating abnormal returns later in the article.

[25]As is well known, the secondary corporate bond market in general exhibits thin trading; that is, 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.

[26]We use the cross-sectional standard deviation to scale the abnormal returns. Ederington, Guan, and Yang (2015) recommend using both cross-sectional and time series measures of standard deviation, but given that we use quarterly data over 9 years, we do not have enough time series observations to incorporate a time series standard deviation for the first part of our sample period.

Table 4
Average Abnormal Returns Based on Transaction Prices for Portfolios Formed Based on LSV Correlated Trading Measures

Panel A	Avg # of Bonds	Average BHM (%)	Average Abnormal Returns: Qtr Prior (%)	Portfolio Frmtn Qtr (%)	Qtr After (%)
Buy portfolios					
LSV_B1	55	−9.7	0.01	0.03	−0.40**
LSV_B2	57	−0.1	−0.12	−0.08	−0.25*
LSV_B3	57	10.0	−0.19*	−0.08	−0.26
LSV_B4	56	20.9	−0.28	0.13	−0.10
LSV_B5	55	36.2	−0.18	0.17	−0.06
LSV_B5–LSV_B1			−0.20	0.14	0.34
LSV_B4–LSV_B1			−0.29	0.10	0.30**

Panel B	Avg # of Bonds (%)	Average SHM (%)	Qtr Prior (%)	Portfolio Frmtn Qtr (%)	Qtr After (%)
Sell portfolios					
LSV_S1	57	−11.1	−0.03	−0.34*	−0.28*
LSV_S2	59	−1.1	−0.32***	−0.46**	−0.31**
LSV_S3	57	8.9	−0.68***	−0.66**	−0.53***
LSV_S4	56	20.7	−0.61***	−1.12***	−0.28
LSV_S5	52	29.8	−1.41***	−1.14***	−0.71**
LSV_S5–LSV_S1			−1.39***	−0.80	−0.43
LSV_S4–LSV_S1			−0.59*	−0.78	0.00

Note: Average abnormal returns for 10 portfolios formed in each of 36 quarters from the first quarter of 2003 through 2011. LSV_B1 (LSV_B5) consists of bonds with the lowest (highest) LSV buy measures during each quarter and LSV_S1 (LSV_S5) consists of bonds with lowest (highest) LSV sell measures during each quarter. Abnormal returns are calculated using 34 benchmark portfolios as described in the text and winsorized at the 1 and 99 percent values. Statistical significance is based on a sign-rank test of standardized abnormal returns.

Our focus is on the difference in the abnormal returns between the portfolios with high buy (sell) correlated trading, that is, B5 and B4 (S5 and S4) and the portfolio with the lowest buy (sell) measures, that is, B1 (S1). In other words, we are primarily interested in the differential impact of high buy (sell) correlated trading versus low buy (sell) correlated trading 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.

TABLE 5
Average Abnormal Returns Based on Transaction Prices for Portfolios Formed Using Correlated Trading Measures Based on Insurer Volume

			Average Abnormal Returns		
Panel A	Avg # Bonds	Average BHM (%)	Qtr Prior (%)	Portfolio Frmtn Qtr (%)	Qtr After (%)
Buy portfolios					
VOL_B1	49	10.7	−0.13	−0.20**	−0.28
VOL_B2	50	32.9	−0.28*	0.16	−0.20
VOL_B3	50	57.5	−0.21	0.01	−0.17*
VOL_B4	48	83.0	−0.28*	0.15	-0.17
VOL_B5	51	99.1	−0.12	0.13	−0.05
VOL_B5–VOL_B1			0.01	0.33**	0.22
VOL_B4–VOL_B1			−0.14	0.35*	0.11
Panel B	Avg # Bonds (%)	Average SHM (%)	Qtr Prior (%)	Portfolio Frmtn Qtr (%)	Qtr After (%)
Sell portfolios					
VOL_S1	64	13.7	−0.05	−0.20**	−0.42***
VOL_S2	64	42.4	−0.15**	−0.59***	−0.16
VOL_S3	64	70.5	−0.43***	−0.71***	−0.39*
VOL_S4	52	91.7	−0.70***	−0.64***	−0.48***
VOL_S5	69	99.8	−1.09***	−1.03***	−0.62***
VOL_S5–VOL_S1			−1.05**	−0.83*	−0.19
VOL_S4–VOL_S1			−0.65***	−0.44	−0.06

Note: Average abnormal returns for 10 portfolios formed in each of 36 quarters from 2003 through 2011. VOL_B1 (VOL_B5) consists of bonds with the lowest (highest) volume-based buy measures during each quarter and VOL_S1 (VOL_S5) consists of bonds with lowest (highest) volume-based sell measures during each quarter. Abnormal returns are calculated using 34 benchmark portfolios as described in the text and winsorized at the 1 and 99 percent values. Statistical significance is based on a sign-rank test of standardized abnormal returns.

Results

Consider Panel A of Table 4. For most of the buy portfolios, the abnormal returns are insignificantly different from zero in each of the three quarters (before, during, after). The exceptions are that the low correlated buy portfolios (LSV_B1 and LSV_B2) have negative abnormal returns in the quarter after portfolio formation.

Turning attention to the difference between the high and low correlated buy portfolios, the abnormal returns for the high correlated buy portfolios, LSV_B5 and LSV_B4 are not statistically different from the abnormal returns for the low correlated buy portfolio (LSV_B1) in any of the time periods, except for subsequent quarter. The difference in abnormal returns between LSV_B4 and LSV_B1 is positive and statistically significant, which suggests that on average returns increase following high correlated buy trading compared to low correlated buy trading. This is the opposite of what is predicted in Price Reversal Hypothesis (H6). If high correlated buy trading temporarily pushed prices above fundamental values, then we would expect prices to rebound subsequently, but we find the opposite.

Panel B of Table 4 presents the abnormal returns for the correlated sell portfolios. For each portfolio, abnormal returns are negative in each quarter (before, during, after) and statistically significant in most cases. This indicates that (1) correlated selling generally occurs after negative returns (consistent with the Momentum Trading Hypothesis (H5)), (2) returns also tend to be negative in the quarter in which correlated selling occurs, and (3) returns continue to be negative in the quarter after correlated selling. The negative returns following correlated selling is not consistent with the Price Reversal Hypothesis (H6). Again, if correlated selling temporarily pushes prices below fundamental values, then one would expect a price reversal, but we do not find this.

Focusing on the difference between the high and low correlated sell portfolios, we find that the high correlated sell portfolios, LSV_S5 and LSV_S4, have abnormal returns that are statistically different from the abnormal returns for the low correlated sell portfolio (LSV_S1) in the quarter prior to portfolio formation. The difference in the abnormal return between LSV_S5 and LSV_S1 is −1.39 percent, which is large economically and statistically significant at the 1 percent level. This finding indicates that bonds in which insurers exhibit strong correlated selling tend to have lower returns in the prior quarter than bonds in which insurers do not exhibit high correlated selling, which is consistent with Momentum Trading Hypothesis (H5) that correlated selling occurs in bonds that have recently performed poorly.

For the portfolio formation quarter, the difference in abnormal returns between LSV_S5 and LSV_S1 and also between LSV_S4 and LSV_S1 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 low correlated selling. Indeed, the LSV_S5–LSV_S1 portfolio continues to have negative abnormal returns in 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 correlated buying is defined using volume are presented in Panel A of Table 5. Again, we focus on the difference between the high buy portfolios (B5 and B4) and the low buy portfolio (B1). Consistent with the previous results, this evidence indicates that buy correlated trading is not associated with abnormal returns in the prior quarter. However, we find positive abnormal returns in the quarter in which correlated buying takes place, but no subsequent reversal. This pattern is consistent with correlated buying helping to incorporate information into prices.

Panel B of Table 5 provides the results using correlated selling based on volume. The results indicate negative abnormal returns in the quarter prior to portfolio formation, which is consistent with the Momentum Trading Hypothesis (H5), that is, momentum selling by insurers following poor returns. There is also evidence of negative abnormal returns in the correlated trading quarter. Again, we do not find abnormal performance in the subsequent quarter when correlated trading is defined using volume. Thus, the evidence is not consistent with the Price Reversal Hypothesis (H6); insurer correlated selling does not push prices temporarily below fundamental values.

Our results differ from Cai et al. (2019) who find significant price reversals following sell-side correlated trading by mutual funds, pension funds, and insurance companies. In light of Cai et al.'s results, we conduct a number of robustness checks:

1. We extended our postcorrelated trading period to two quarters and also to three quarters, but we still do not find evidence of reversals.
2. The analysis above uses transaction prices to calculate abnormal returns, whereas Cai et al. (2019) use Merrill Lynch quoted prices. To explore whether transaction prices versus quoted prices explain the different results, we gather 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. To conserve space, we do not tabulate the results. Although the statistical significance of the results using quoted prices differ somewhat from our baseline results (presented in Tables 4 and 5), the implications are similar; that is: (1) correlated selling is preceded by negative abnormal returns; (2) during the quarter in which correlated selling takes place, there is evidence of positive abnormal returns for correlated buying and negative abnormal returns for correlated selling; and (3) there is no evidence of price reversals in the subsequent quarter. 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. and we are using a reduced sample size.
3. We also redo our analysis using other abnormal return measures. First, we use raw returns. Again, to conserve space we do not tabulate the results. 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 correlated selling portfolios relative to the low correlated selling portfolios using both the LSV and the volume-based measures. In only one instance, however, is the difference between the high and low correlated selling portfolios statistically significant at the 10 percent level.[27] Given the

[27]Another possible explanation for the different results is that the method of testing for statistical significance differs between the two studies. As noted earlier, we use the cross-

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.

Second, we use the Fama–French five-factor bond model (Fama and French, 1993) to measure the average abnormal return on the four portfolios based on the LSV measure: (LSV_B5−LSV_B1), (LSV_B4–LSV_B1), (LSV_S5–LSV_S1), (LSV_S4–LSV_S1) and for the corresponding four portfolios for the volume-based measure.[28] For each quarter, we form the eight portfolios and calculate the return on the portfolio as the equally weighted average return on the securities in the portfolio (R_{Pt}) in excess of the risk-free rate for the quarter prior to, the quarter of, and the quarter subsequent to the portfolio formation quarter. Repeating this for each quarter in the sample gives a time series of excess returns for each of the eight portfolios over three different quarters. The estimate of the average abnormal return on each of the eight portfolios for the quarter before, during, and after portfolio formation is the estimated intercept from the following five-factor model:

$$R_{Pt} - R_{ft} = \alpha + \beta_M(R_{\underline{m}t} - R_{ft}) + \beta_S SMB_t + \beta_H HMT_t + \beta_T Term_t + \beta_D DEF_t + \varepsilon_{pt},$$

where the dependent variable, R_{Pt}–R_{ft}, is the excess return on portfolio P (one of the eight portfolios) in quarter t for the quarter before, during, or after portfolio formation. The risk-free rate, market return, small minus big (SMB) factor, high minus low (HML) factor are from Ken French's Web site.[29] The default spread (DEF) is the average yield spread between Moody's BBB and AAA corporate bonds over a quarter, and the term spread (TERM) is the average yield spread between 3-month and 10-year Treasury constant maturity rate over a quarter.

The results, which are not tabulated here but are available in the Online Appendix (Table A2) generally reinforce the inferences drawn from the prior results. There is evidence of positive abnormal returns prior to correlated buying and positive but statistically insignificant abnormal returns during the correlated buying quarter. For the quarter after correlated buying, in three of the four portfolios, the average abnormal returns are small in magnitude and statistically insignificantly different from zero. However, the one exception to the previous evidence is that one of the volume-based correlated buy portfolios has a negative and statistically significant

sectional standard deviation to scale the abnormal returns when testing for statistical significance (see Ederington, Guan, and Yang, 2015). If we do not standardize abnormal returns, then the raw returns in the quarter after correlated selling are statistically significant at the 5 and 10 percent levels.

[28]Bessembinder et al. (2009) focus on three methods for measuring abnormal bond returns. One is the matching portfolio method, which is essentially what was presented earlier. A second approach, which is a simplification of the first approach, is simply subtracting the return on a Treasury bond with a similar maturity. The third approach is the factor model approach, which we now present.

[29]Portfolio returns are constructed using prices from TRACE. Quarterly bond returns are computed using the average trade price at the last day of the quarter and we take into accrued interest and coupon payment. We convert monthly factors to quarterly factors.

average abnormal return, which is consistent with a price reversal in the subsequent quarter.

The correlated sell portfolio results indicate large negative abnormal returns in the portfolio formation quarter, consistent with selling pushing prices lower. However, we see no evidence of prices reversals for the sell portfolios; instead, average abnormal returns are negative and statistically significant in the quarter following correlated selling.

Abnormal Returns on Bonds in Which SIFIs Are Engaged in Correlated Trading

We now examine whether the impact of correlated trading on bond prices differs when the bonds are more heavily traded by SIFIs. This analysis is motivated in part by the fact that the 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 correlated trading 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 group consists of all of the other bonds. We also used a 25 percent cutoff to define the SIFI group and found similar results.

We discuss results using the volume-based measure, but the results are similar if we use the LSV measure. Within each group, the bonds with nonmissing buy measures are evenly divided into three portfolios. Portfolio BP3 consists of the bonds with the highest one-third of the buy measures and portfolio BP1 consists of the bonds with the lowest one-third of buy measures. For both the SIFI and non-SIFI groups, we examine the difference in the abnormal returns between BP3 and BP1. Similarly, the bonds with nonmissing sell measures are evenly divided into three portfolios, with SP3 (SP1) being the portfolio with the highest (lowest) one-third sell measures. For both the SIFI and non-SIFI groups, we examine the difference between the abnormal returns of SP3 and SP1.[30]

We do not tabulate the results here but they are available in the Online Appendix (Table A3). The main result is that during the portfolio formation quarter, the high sell portfolio performs worse than the low sell 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 1 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.[31]

[30]We use 6 as opposed to the 10 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 into two groups based on whether the bonds were traded heavily by SIFIs.

Thus, our evidence indicates that the prices of bonds in which correlated trading takes place fall on average during the correlated trading period when SIFI insurers are heavily involved in trading, but prices do not fall on average when SIFIs are not heavily involved in trading. Stated differently, when correlated trading 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 bond prices temporarily below fundamental values is inconsistent with our findings of no rebound in the price in the subsequent quarter.[32]

SUMMARY AND IMPLICATIONS FOR THE SYSTEMIC RISK OF LIFE INSURERS

Using two different measures, we find that U.S. life insurers' investment decisions in corporate bonds are consistent with correlated trading. That is, on average life insurers tend to be on the same side of the market (either buying or selling) in individual corporate bonds more than would be expected if their investment decisions were independent of each other. Correlated sell trading among insurers is more pronounced in smaller bonds, lower rated bonds, and bonds that have been downgraded. In addition, insurers with relatively high RBC ratios are more engaged in correlated selling of downgraded bonds than are insurers with lower RBC ratios. Correlated trading is also more pronounced when insurers that are part of groups that have been designated as 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, e.g., Financial Stability Oversight Council, 2013; Schwarcz and Schwarcz, 2014; Getmansky et al., 2016; Paulson and Rosen, 2016). The evidence that insurers exhibit correlated trading therefore lends credence to the argument that life insurers' investment activities

[31]We also investigated whether these findings differ during the financial crisis versus non-financial crisis periods. The difference in abnormal returns between the high-sell and low-sell portfolios when the bonds are heavily traded by SIFIs is primarily due to the noncrisis period.

[32]One might argue that if insurer correlated trading 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 main takeaway from this is analysis is the large negative abnormal return during the financial crisis for the bonds with high correlated selling (S5) relative to bonds with low correlated selling (S1) during the quarter prior to the correlated selling. The difference in these portfolios is −3.77 percent when the LSV measures are used and −2.58 percent with the volume-based measure. Thus, the evidence suggests that correlated selling following poor bond performance was especially pronounced during the financial crisis. The abnormal return results during the financial crisis for the quarter after correlated selling occurs are mixed. For example, using the LSV measure, the differences between the abnormal returns for the high-sell portfolios and the low-sell portfolio, S5–S1 and S4–S1, are −0.90 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.

could be a source of systemic risk. However, correlated trading does not imply that life insurers' investment decisions have an adverse impact on market prices. Thus, we also examine the relationship between correlated trading and bond abnormal returns. We find that correlated selling follows poor bond performance, which would suggest that correlated selling could potentially exacerbate price declines. However, based on abnormal returns during the quarter in which correlated trading takes place and in the subsequent quarter, we find little evidence that insurer correlated trading causes prices to move away temporarily from fundamental values during our sample period.

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

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