Portfolio Similarity and Asset Liquidation in the Insurance Industry*

Giulio Girardi† Kathleen W. Hanley‡ Stanislava Nikolova§
Loriana Pelizzon¶ Mila Getmansky Sherman‖

This Draft: March 4, 2019

Abstract

An important assumption underlying the designation of some insurers as systemically important is that their overlapping portfolio holdings can result in common selling. We measure the overlap in holdings using cosine similarity, and show that insurers with more similar portfolios have larger subsequent common sales. This relationship can be magnified for some insurers when they are regulatory capital constrained or markets are under stress. When faced with an exogenous liquidity shock, insurers with greater portfolio similarity have even larger common sales that impact prices. Our measure can be used by regulators to predict which institutions may contribute most to financial instability through the asset liquidation channel of risk transmission.

Keywords: Interconnectedness, Asset Liquidation, Similarity, Financial Stability, Insurance Companies, SIFI

JEL Classification: G11, G18, G2

*We thank Sergey Chernenko, Rama Cont, Andrew Ellul, Isil Erel, Mark Flannery, Robin Greenwood, Harald Hau, Pab Jotikasthira, Anastasia Kartasheva, Ralph Koijen, Yijia Lin, Albert J. Menkveld, Alessandro Sbuelz, and participants at the American Finance Association Meeting (AFA 2017), IIF Colloquium on International Insurance Regulatory Issues, London Quantitative Finance Seminar, MIT CSRA Meeting, Temple University Workshop on Systemic Risk and the Insurance Industry, and seminars at Arizona State University, Ohio State University, U.S. Securities and Exchange Commission, and University of Massachusetts-Amherst for helpful comments. We thank Silvia Dalla Fontana, Nicola Mano, Max Riedel, and Matteo Sottocornola for excellent research support. We are grateful to the SAFE Center, funded by the State of Hessen initiative for research, LOEWE, for their financial support. The Securities and Exchange Commission, as a matter of policy, disclaims responsibility for any private publication or statement by any of its employees. The views expressed herein are those of the authors and do not necessarily reflect the views of the Commission or of the authors' colleagues on the staff of the Commission.

†Division of Economic and Risk Analysis, U.S. Securities and Exchange Commission, Washington, DC 20549-9040. Email: girardig@sec.gov.

‡College of Business and Economics, Lehigh University, Bethlehem, PA 18015. Email: kwh315@lehigh.edu.

§College of Business, University of Nebraska–Lincoln, Lincoln, NE 68588. Email: snikolova2@unl.edu.

¶SAFE-Goethe University Frankfurt, Theodor-W.-Adorno Platz 3, 60323 Frankfurt am Main. Email: pelizzon@safe.uni-frankfurt.de.

‖Isenberg School of Management, University of Massachusetts, Amherst, MA 01003. Email: msherman@isenberg.umass.edu.

"The severity of the disruption caused by a forced liquidation of Prudential's assets could be amplified by the fact that *the investment portfolios of many large insurance companies are composed of similar assets*, which could cause significant reductions in asset valuations and losses for those firms. The erosion of capital and potential deleveraging could result in asset fire sales that cause significant damage to the broader economy." (italics added)

Basis for the Financial Stability Oversight Council's Final Determination Regarding Prudential Financial, Inc.

1 Introduction

The global financial crisis of 2007-2009 exposed many vulnerabilities within the financial system. It highlighted how interconnectedness among financial entities contributed to the collapse of prominent institutions (e.g., Lehman Brothers, Bear Stearns, Washington Mutual, and Wachovia) and to disruptions in financial markets (e.g., stock, credit default swap, sub-prime mortgage, and money markets). In response, the U.S. Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. The Act created the Financial Stability Oversight Council (FSOC) and endowed the Council with the authority to implement enhanced prudential standards for bank and nonbank entities designated as Systemically Important Financial Institutions (SIFIs).[1]

In designating certain large insurers as SIFIs, the FSOC expressed a concern that because insurers hold similar portfolios, the need to liquidate similar assets quickly "would cause a fall in asset prices and thereby significantly disrupt trading ... or cause significant losses or funding problems for other firms with similar holdings."[2] This concern is echoed by Kartasheva (2014) who argues that insurers do not need to fail to propagate risk throughout the financial system; it may be sufficient for them to "fire sell" assets to produce a significant effect.[3] While there is evidence

[1]As noted in the final rule on the *Authority to Require Supervision and Regulation of Certain Nonbank Financial Companies*, "Section 113 of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Pub. L. 111-203, 124 Stat. 1376 (2010)) authorizes the Financial Stability Oversight Council to determine that a nonbank financial company shall be supervised by the Board of Governors of the Federal Reserve System and shall be subject to prudential standards... if the Council determines that material financial distress of the nonbank financial company, or the nature, scope, size, scale, concentration, interconnectedness, or mix of the activities of the nonbank financial company, could pose a threat to the financial stability of the United States." Similar criteria are used internationally by the Financial Stability Board to designate global systemically important financial institutions (G-SIFIs) (see BIS (2014)).

[2]See *Basis for the Financial Stability Oversight Council's Final Determination Regarding Prudential Financial, Inc.* available on the FSOC website (FSOC (2013)). The FSOC originally designated four nonbank financial institutions (three of them are insurance companies) as SIFIs: MetLife, Inc.; American International Group, Inc. (AIG); General Electric Capital Corporation, Inc. (GECC); and Prudential Financial, Inc. The Council has since rescinded both AIG's and GECC's SIFI status because of changes the companies made in response to the designation. MetLife's designation was overturned by the courts citing improper economic analysis.

[3]Other risks and activities such as operational risks, reinsurance, non-traditional investments, and financing of insurers have been discussed as affecting financial stability. See Harrington (2009) and Cummins and Weiss (2014) regarding the effect of potential policyholder withdrawals during a financial crisis, Koijen and Yogo (2016) for a

that fire sales by insurers can depress individual sold securities' prices (Ellul et al. (2011), Merrill et al. (2013), and Manconi et al. (2012)), idiosyncratic selling does not necessarily impact financial stability. Instead, selling must be correlated in order to affect large segments of the market or the market as a whole. There is, however, no empirical evidence that insurers' overall portfolio similarity leads to more correlated selling and that such selling impacts prices.

In this paper, we address this gap in the literature by investigating whether insurers with more similar portfolios sell more in common. Using cluster analysis, we document that the composition of insurers' holdings is very similar and stable through time. Insurer portfolios can be characterized by three distinct allocation strategies: 1) diversified across corporate bonds, municipal bonds, and government sponsored entity (GSE) fixed-income securities; 2) concentrated in corporate bonds; and 3) concentrated in equity.

Next, we develop a measure of portfolio similarity, between a pair of insurers, based on the cosine similarity of their holdings using 2002–2014 security-level data from the National Association of Insurance Commissioners (NAIC). Cosine similarity is easily interpretable since it is bounded between zero and one. Two insurers with identical portfolios will have a cosine similarity equal to one; and if the portfolios are completely different, the cosine similarity will equal zero. We calculate cosine similarity across asset classes or security issuers held by a pair of insurers. We show that an insurer pair's portfolio similarity is related to pairwise insurer characteristics such as joint size, portfolio concentration, and business line similarity.

We then document that our measure of portfolio similarity can predict the incidence and amount of common sales. We use quarterly buy and sell transactions to construct a measure of common sales as the dot product of an insurer pair's dollar net sales (sales minus purchases) at both the asset class and security issuer level. We show that there is a strong positive relationship between a pair's portfolio similarity and its quarterly common sales during the following year. Consistent with regulatory concerns, we find that Potentially Systemically Important Financial Institutions (PSIFIs), defined as having more than $50 billion in total assets, have greater common sales. However, the positive relationship between size and common sales holds true in general, which suggests that the $50 billion threshold used by FSOC does not identify the full set of insurers that

discussion of the risks of shadow reinsurance, Geneva Association (2010) and Grace (2010) about the consequences of insurers' increased exposure to derivatives, and Geneva Association (2010) concerning the impact of insurers' increased reliance on short-term funding.

may contribute to asset liquidation vulnerabilities.

We show that portfolio concentration has a negative relationship with portfolio similarity and common sales, even though some have suggested that it could be a useful metric for identifying SIFIs (Haldane and May (2011), Gai et al. (2011), and Allen et al. (2012)). Our findings support the concerns of Castiglionesi and Navarro (2008), Wagner (2010), Wagner (2011), Ibragimov et al. (2011), and Cont and Wagalath (2016) who suggest that although portfolio diversification reduces each institution's individual probability of failure, it can make the potential for common selling higher.

We provide evidence that public market information, such as return covariance, cannot substitute for portfolio similarity in predicting common selling. A number of recent papers have proposed return covariance as a measure of interconnectedness among financial institutions (Billio et al. (2012), Neale et al. (2012), and Brunetti et al. (2018)). However, we find that the return covariance of a pair of publicly traded insurers has either no relationship or a negative relationship with common sales at both the asset class and issuer levels. Thus, while return covariance may be a useful metric of assessing some aspects of financial institutions' interconnectedness, it does not appear to reflect the type of commonality that can contribute to risk transmission through the asset liquidation channel.

We investigate whether our finding of a positive relationship between portfolio similarity and common sales is due to the liquidity or credit quality of common holdings, since these asset characteristics have been shown to impact insurers' selling decisions when faced with regulatory capital constraints (Ellul et al. (2011) and Ellul et al. (2015)). We decompose portfolio similarity into the similarity of 1) liquid and illiquid asset classes, and 2) downgraded and non-downgraded issuers.[4] We document that our results are not driven by differences in the liquidity or credit quality of holdings.

We examine whether certain circumstances may magnify the relationship between portfolio similarity and common sales. For example, it may be the case that the relationship is stronger

[4]We classify as liquid the following asset classes: equity (all industries), mutual fund shares, US government securities, GSE debt and asset-backed securities, and sovereign bonds. We classify as illiquid the following asset classes: corporate bonds (all industries), municipal bonds (all types), residential mortgage-backed securities, commercial mortgage-backed securities, and all other non-mortgage asset-backed securities. Downgraded (not downgraded) issuers are issuers that are (are not) downgraded from investment grade to non-investment grade in the year after being held.

when both insurers in a pair face regulatory capital constraints or during times of market stress. We first determine the extent to which an insurer is regulatory capital constrained by whether its risk-based capital ratio (RBC) is in the bottom quartile of the sample. Consistent with the prior literature, we find that insurer pairs with low RBC sell more asset classes and issuers in common. Moreover, capital constraints magnify the effect of portfolio similarity on common sales at the asset class, but not at the issuer level. Overall, one could interpret our findings on the magnifying effect of regulatory capital constraints as evidence that some insurers may have had less leeway in which asset class to dispose of, but not which issuer.

Although the similarity in portfolio holdings predicts common sales, it may not necessarily affect asset prices. To test the relationship between portfolio similarity and price changes, we examine an shock to the liquidity needs of insurers in the aftermath of the Lehman failure and Hurricanes Katrina and Rita. In the September of 2008, the banking industry's balance sheets came under severe distress and AIG's exposure to credit default swaps lead to its bailout by the federal government. During this time, both banks and AIG were forced to liquidate holdings to shore up regulatory capital. Thus, the advent of the financial crisis provides us with a potential outside shock to insurers' liquidity needs and allows us to study the link between similar holdings and the price impact of potentially forced common sales. Examining potential commonality in sales, we find that insurer pairs with greater portfolio similarity and exposure to either bank debt or AIG have greater common sales in the third and fourth quarters of 2008 around the bankruptcy of Lehman.

During the quarter in which the hurricanes took place, many P&C insurers with exposure in hurricane-affected states were forced to liquidate holdings to cover policyholder losses. Examining the effect of the hurricanes on P&C insurers, we document that during the quarter of the hurricanes, portfolio similarity increases common sales more for exposed insurer pairs compared to all other pairs. Thus, common sales are more likely to occur for affected insurers in times of crisis.

To determine whether this results in a price impact, we examine the change in the value of an exposed pair's joint corporate bond holdings. Specifically, for each pair we construct the weighted average yield spread change of its joint portfolio from the quarter before to the quarter after either the Lehman failure or the time period of the hurricanes. Regardless of whether we are using exposure to the banking sector, AIG, or the hurricanes, we find that exposed pairs with greater portfolio similarity experience a larger increase in the yield spread of their corporate bond holdings compared to non-exposed pairs during the event. We, therefore, conclude that the similarity of insurers' holdings may lead to common sales with the potential to depress asset prices under certain circumstances.

Finally, we propose an insurer-level portfolio similarity measure, computed as the average portfolio similarity of an insurer with all other insurers in our sample, to identify specific institutions that might contribute to the asset liquidation channel of risk transmission. We show that this measure can be used to predict the extent to which an individual insurer will sell more in common with all other insurers even after controlling for the insurer's own sales and size. This suggests that the measure can be used in tandem with other risk metrics to identify insurers that may contribute to financial instability.

This paper adds to a growing literature on whether institutional investors' herding in securities and asset liquidation impacts asset prices. Prior studies focus on traded corporate bonds and document that under certain circumstances herding can put downward pressure on prices. For example, Ellul et al. (2011) find that when a bond is held by more regulatory constrained insurers, the effect of a fire sale on bond prices is more pronounced. Nanda et al. (2017) document that the proportion held by insurance companies of a particular bond has explanatory power for yield spreads. Chaderina et al. (2018) show that P&C insurers tend to sell liquid bonds during times of stress and the more commonly held the bond, the greater the price impact of sales. Chiang and Niehaus (2016) document that life insurers tend to herd when buying and selling corporate bonds, and show that bond returns are abnormally low during the quarter when life insurers exhibit high sell-side herding. Finally, F. Cai et al. (2018) conclude that insurance companies have a greater tendency to herd than mutual funds and pension funds, and institutional sell herding in corporate bonds can be price destabilizing.

In contrast to the above studies, our finding that greater portfolio similarity results in larger common sales, extends to the entirety of insurers' portfolios, instead of being limited to just a particular asset class or periods of market stress. This is an important distinction for several reasons. First, publicly traded corporate bonds comprise only a fifth of the assets held by the insurance industry.[5] Second, during the financial crisis, the downgrade and subsequent sales of

[5] According to data from insurers' NAIC filings on Schedule D and from TRACE, in 2014 life and P&C insurers

fixed income securities other than corporate bonds (e.g. mortgage-backed securities) contributed to the transmission of risk across these securities' common holders. And finally, insurers may strategically trade across asset classes to mitigate the price impact of sales (Ellul et al. (2015)). For all of these reasons, considering all asset classes in insurers' portfolios when establishing a link between portfolio similarity and common sales is important.

In addition, while prior studies examine the impact of insurers' herding on individual corporate bond prices, we document an impact on the value of their corporate bond portfolios. This suggests a feedback effect from investors to asset prices and then back to investors that could be particularly destabilizing. Thus, our portfolio measure can be used by financial stability regulators to identify institutions that may not only affect, but also be affected by, the asset liquidation channel of risk transmission.

Finally, unlike other interconnectedness metrics that rely on equity returns, our measure of portfolio similarity can be used to assess the potential for common selling of any financial institution that discloses holdings even when the institution is not publicly traded. In particular, the measure can be applied to the portfolio holdings of banks (J. Cai et al. (2018)), hedge funds (Sias et al. (2016)), and money market funds, to name a few, allowing regulators to monitor the potential for common sales spillover from a wide variety of market participants.

2 Data

2.1 Data Sources and Sample Construction

We analyze the portfolio similarity and selling behavior of insurers from 2002 to 2014 using information from their statutory filings with the NAIC as distributed by A.M. Best. For each insurer, Parts 1 and 2 of Schedule D of these filings list the par value and book value of every security held at calendar year-end. We retain all non-negative annual holdings. Parts 3, 4 and 5 of Schedule D list every security an insurer disposed of or purchased during the year along with its par value, disposal/purchase value, and date of disposal/purchase. We exclude any security disposals due to maturity, repayment, calls, or other non-trading activity.

held \$1.36 trillion of publicly traded corporate bonds (corporate bonds that trade at least once in 2014). The Federal Reserve's Flow of Funds tables indicate that in 2014 these insurers held \$6.3 trillion of debt and equity securities.

Portfolio holdings, sales, and purchases are reported at the individual security (9-digit CUSIP) level. For each insurer, we aggregate this information to both the issuer level and to the asset class level. We utilize the first 6 digits of each CUSIP as the issuer identifier and aggregate the holdings, sales and purchases of securities with the same 6-digit CUSIP.[6] When aggregating, we use the par value of fixed-income holdings. Since no comparable number exists for equity securities, we aggregate their book values. We construct quarterly net sales at the issuer level as sales minus purchases, excluding negative values.

In order to aggregate holdings, sales, and purchases to the asset class level, we categorize each security into one of ten primary asset classes: (1) U.S. government securities, (2) GSE debt and asset-backed securities, (3) municipal bonds, (4) sovereign bonds, (5) corporate bonds, (6) RMBS, (7) CMBS, (8) ABS other than RMBS/CMBS, (9) equity (common and preferred stock), and (10) mutual fund shares. We identify RMBS and CMBS using the NAIC-provided list of PIMCO- and BlackRock-modeled securities.[7] We classify all remaining fixed-income securities using the following sources sequentially: (1) the sector and subsector codes in S&P RatingXpress, then (2) the type and subtype codes in DataScope, then (3) the issue description and issuer name in NAIC Schedule D, and finally (4) the issuer name and collateral asset type in SDC Platinum's New Issues Module. We further refine corporate bonds, municipal bonds, and equity using the issuer's industry or sector information reported in Schedule D. We categorize corporate bonds and equity as undefined if issuer industry or sector is missing or conflicting. This process yields 34 unique asset classes listed in Appendix A. We then aggregate holdings and net sales (sales minus purchases with negative values excluded) by asset class.

Although Schedule D is filed by each individual insurer, the predominant organizational structure in the insurance industry is the insurance group. Individual companies operate independently in many ways, but some aspects of their operations are centrally managed, including investment decisions, thus creating strong connections among the members of a group. We, therefore, conduct our analysis at the group level rather than at the individual insurer level. To do so, we aggregate

[6]The use of the 6-digit CUSIP only approximates the ultimate issuer of the securities as a parent company may have different 6-digit subsidiary CUSIPs.

[7]The NAIC changed its capital assessment methodology for certain asset classes by replacing credit ratings as the measure of expected loss with valuation-based loss estimates from PIMCO for RMBS and BlackRock for CMBS. The NAIC publishes the list of PIMCO- and BlackRock-modeled securities annually. For more information on this regulatory change, see Hanley and Nikolova (2017).

holdings, net sales, and balance sheet information of the initial sample of 5,369 individual insurers to the group level. This aggregation results in a sample of 2,812 different insurance groups. We refer to these as “insurers” throughout the remainder of the paper.

For some of our analysis, we require stock return data, which is only available at the holding company level. Typically, a holding company owns several insurer groups. To aggregate Schedule D and balance sheet data to the holding company level, we match insurer groups to company names in the CRSP/Compustat Merged database and find matches for 107 holding companies. For each holding company, we collect daily holding period returns from the CRSP database.

We also categorize insurers as P&C, life, or other (e.g., health, fraternal, and title) if at least half of an insurer's portfolio assets are held in a given year by companies in the group that are in that line of business. Our sample includes 1,746 P&C and 635 life insurers.

Finally, in order to examine whether systemically important insurers are more likely to have similar portfolios and sell similar assets, we also classify insurers as Potentially Systemically Important Financial Institutions (or PSIFIs) if they have more than $50 billion in total assets, excluding assets held in separate accounts, in at least one year of the sample period. Based on this size threshold, we identify 38 insurers as potential candidates for SIFI designation by the FSOC.

2.2 Portfolio Composition Summary Statistics

Table 1 presents descriptive statistics for our sample of insurers with detailed variable definitions provided in Appendix B. For each insurer, we compute the time-series average of each variable across the sample period and then report the cross-sectional mean, median, and standard deviation. The average total assets of sample insurers, excluding assets held in separate accounts, are $2.41 billion. Life insurers ($7.54 billion) are much larger than P&C insurers ($0.85 billion).[8] By construction, PSIFIs have significantly more assets ($99.8 billion) compared to non-PSIFIs ($0.87 billion).[9] The average insurer's investment portfolio is $1.65 billion. As with total assets, life insurers have larger investment portfolios than P&C insurers, and PSIFIs have larger investment portfolios than non-PSIFIs.

[8] The number of insurers in the “other” category is small, so we do not report summary statistics separately for this type.

[9] The number of PSIFIs and non-PSIFIs does not add up to the total number of insurers, because our PSIFI classification requires data on total assets, which are not available for all insurers in the sample.

The table also presents insurers' portfolio composition by asset class. Consistent with the common perception that insurers are important investors in fixed-income markets, we find that fixed-income securities make up 81% of insurer holdings on average. Corporate bonds (27%), GSE debt and asset-backed securities (19%), municipal bonds (14%), and U.S. government securities (15%) represent the largest proportion. Equity holdings are primarily in the form of common and preferred stock, and these securities account for 14% of the portfolio, on average. Insurers also hold mutual fund shares and these comprise 5% of average holdings.

Portfolio composition differs by line of business and PSIFI status. Life insurers tend to invest a greater proportion of their portfolio in corporate bonds while P&C insurers hold more municipal bonds and mutual fund shares. PSIFIs invest primarily in corporate bonds (52.7%), and compared to non-PSIFIs, invest in more illiquid asset classes such as RMBS, CMBS, and ABS. Non-PSIFIs have portfolios that are more balanced among corporate bonds, GSE debt and asset-backed securities, municipal bonds, U.S. government securities, and equity.

Figure 1 summarizes the time-series variation of the insurance industry's aggregate holdings and indicates that only small shifts in and out of asset classes occur through time. Over our sample period, the proportion of insurer portfolios allocated to U.S. government securities increases slightly. The figure also shows that insurers' holdings of RMBS and CMBS increase in the period leading up to the financial crisis and then gradually decrease consistent with the evidence presented in Hanley and Nikolova (2017). Thus, aggregate insurer portfolios are relatively stable.

In examining the composition of insurer holdings, we find that the average insurer in our sample holds 380 different securities issued by 250 issuers. The median number of securities or issuers held is less than half of the sample average, implying that some insurers invest in significantly more securities or issuers than others. Life insurers and PSIFIs invest in more securities and issuers than P&C insurers and non-PSIFIs. For instance, PSIFIs hold an average of 3,704 different securities issued by 1,888 issuers compared to an average of 223 securities issued by 172 issuers held by non-PSIFIs.

Finally, we measure the level of portfolio concentration at either the asset class ($Conc\_AC$) or issuer ($Conc\_I$) level using a Herfindahl index, calculated as follows:

$$Conc_{it} = \sum_{k=1}^{K} w_{itk}^2 \tag{1}$$

where w_{itk} is asset class (issuer) k's weight in insurer i's portfolio at the end of year t, and is calculated as the dollar value invested in asset class (issuer) k relative to the total dollar value of the insurer's portfolio. The cross-sectional mean, median, and standard deviation of insurers' time-series averages of the two concentration measures are also reported in Table 1. The average asset class concentration in our sample is 0.31 whereas the average issuer concentration is much smaller at 0.16, which is consistent with the fact that our sample consists of about 32,000 issuers and only 34 asset classes. Life and P&C insurers have similar portfolio concentrations. PSIFIs' portfolios are less concentrated (more diversified) than those of non-PSIFIs at both the asset class and issuer level, which is not surprising given the large size of the average PSIFI's portfolio.

2.3 Cluster Analysis of Portfolio Composition

We next use cluster analysis to examine whether insurers differ in their portfolio allocation strategies and whether their strategies change over time. Cluster analysis allows us to separate insurers into subgroups (clusters) that have closer portfolio connections with each other than with those outside the cluster. We use a standard cluster analysis approach, which we describe in Appendix C. We find that there are three distinct clusters suggesting that insurers employ only a small number of portfolio strategies. This differentiates them from mutual funds, which follow a variety of investment strategies, and provides support for FSOC's assertion that insurers hold similar assets.[10]

The average portfolio composition of the three clusters is displayed in Figure 2. Cluster 1 is relatively diversified across primary asset classes, Cluster 2 is mainly invested in corporate bonds, and Cluster 3 is dominated by equity. In terms of the number of insurers in each cluster, Clusters 1 and 2 are evenly populated with approximately 45% of sample insurers in each cluster. The remaining 10% of insurers are in Cluster 3. If we conduct the cluster analysis by year, the optimal

[10]For example, common mutual fund types based on investment strategy include equity funds (large-cap, mid-cap/small-cap, foreign, emerging markets), bond funds (intermediate, short-term, inflation protected, world), balanced funds, target date funds, and real estate funds.

number of clusters remains at three and the composition of each cluster remains similar.[11]

Finally, there is a clear distinction between the portfolio allocation strategies of PSIFIs and those of non-PSIFIs. Figure 3 shows the distribution of PSIFIs and non-PSIFIs in each cluster. PSIFI's portfolios mostly resemble Cluster 2, which is dominated by corporate bonds. Non-PSIFIs' portfolios are similar to Cluster 1, which is diversified across different primary asset classes. These results are consistent with statistics presented in Table 1.

3 Measures of Portfolio Similarity and Common Sales

In order to test whether insurers with similar portfolios are likely to trade in a related fashion and subsequently affect asset prices, we need measures that capture the overlap in a pair's portfolios and the overlap in a pair's sales. We construct the pairwise portfolio similarity across all types of securities using cosine similarity either at the asset class or issuer level. Cosine similarity is well-suited to comparing the distance between two vectors and in economics has been used in text analytics (Hanley and Hoberg (2010) and Hanley and Hoberg (2012)) and hedge fund portfolio analysis (Sias et al. (2016)).

We begin by calculating the proportional dollar value of each asset class or issuer of securities held in an insurer's portfolio at calendar year-end. The result is a vector of asset class or issuer portfolio weights. For example, the maximum number of unique issuers in a given year is approximately 32,000 and therefore, each insurer's vector of issuer portfolio weights has a length of 32,000. If an insurer does not invest in a particular issuer in a given year, the portfolio weight for that issuer is set to 0. We then calculate the cosine similarity between the portfolios of insurers i and j in year t as the dot product of the pair's portfolio weight vectors normalized by the vectors' lengths. That is,

$$Similarity_{ijt} = \frac{\boldsymbol{w_{it}} \cdot \boldsymbol{w_{jt}}}{\|\boldsymbol{w_{it}}\| \ \|\boldsymbol{w_{jt}}\|} \tag{2}$$

where w_{it} is insurer i's and w_{jt} is insurer j's vector of weights at year-end t. Depending on whether asset class or issuer portfolio weights are used, we refer to this quantity as portfolio similarity at the asset class ($Similarity\_AC$) or issuer ($Similarity\_I$) level.

[11] In unreported results, we find that insurers move infrequently between clusters, consistent with the evidence presented in Figure 1.

Because all portfolio weight vectors have elements that are non-negative, this measure of portfolio similarity is bounded in the interval [0,1]. Intuitively, the portfolio similarity between two insurers is closer to 1 when their holdings are more similar and equals 0 when they are entirely different.

Table 2 provides summary statistics for our portfolio similarity measures for the whole sample of insurer pairs as well as for PSIFI and non-PSIFI pairs. We define the variable *PSIFI_Pair* (*Non-PSIFI_Pair*) equal to 1 if both insurers in a pair are classified as PSIFI (non-PSIFI), and 0 otherwise. The average asset class similarity between a pair of insurers, *Similarity_AC*, is 0.45. PSIFI pairs have on average much larger portfolio similarity at the asset class level (0.65) than non-PSIFIs pairs (0.45). The average similarity between a pair of insurers at the issuer level, *Similarity_I*, is lower (0.12) than at the asset class level, because in our sample there are many more issuers (about 32,000) than asset classes (34). The average issuer-level portfolio similarity is again higher for PSIFI (0.18) than non-PSIFI (0.12) pairs.

Figure 4 depicts the time series of the average pairwise portfolio similarity at the asset class and issuer level for the sample of all insurers and for the subsamples of PSIFI or non-PSIFI pairs. Since non-PSIFI pairs make up the majority of insurers in our sample, their average portfolio similarity closely mimics that of all insurers at both the asset class and issuer level. Non-PSIFIs' average portfolio similarity at the asset class level has declined over the sample period but has remained relatively constant at the issuer level. PSIFI pairs have larger asset class and issuer similarity than non-PSIFI pairs. PSIFI pairs' asset class similarity does not fluctuate much over time, but at the issuer level it has increased. Interestingly, the divergence in portfolio similarity between PSIFIs and non-PSIFIs is larger after the financial crisis.

Prior studies document that insurers consider an asset's liquidity (Ellul et al. (2015)) and credit quality (Ellul et al. (2011)) in their selling decisions when they need to replenish capital and, therefore, these asset characteristics might be important to consider when constructing a measure of portfolio similarity. We disaggregate insurers' holdings into liquid or illiquid asset classes, and downgraded or not downgraded issuers. Liquid asset classes include equity (all industries), mutual fund shares, U.S. government securities, GSE debt and asset-backed securities, and sovereign bonds. Illiquid asset classes include corporate bonds (all industries), municipal bonds (all types), RMBS, CMBS, and ABS. We determine whether or not an issuer is downgraded using credit rating information from DataScope. A downgraded issuer is defined as having at least one of its securities downgraded from investment grade to non-investment grade by S&P, Moody's, or Fitch in the year after an insurer reports holdings it.

Figure 5 shows the proportion of insurer holdings comprised of illiquid asset classes or downgraded issuers. In Panel (a), approximately 70% of holdings are classified as illiquid, and this proportion is relatively constant through time. Panel (b) shows a significant time trend in the proportion of holdings classified as downgraded. Not surprisingly, holdings of downgraded issuers are largest during the financial crisis when they reach approximately 15% of insurers' portfolios.

We then decompose the portfolio similarity between a pair of insurers by recomputing the cosine similarity using only liquid (*Similarity_AC_Liquid*) or illiquid (*Similarity_AC_Illiquid*) asset classes, and downgraded (*Similarity_I_Downgraded*) or not downgraded (*Similarity_I_NotDowngraded*) issuers. Table 2 presents summary statistics for the decomposed similarity measures for all as well as for PSIFI and non-PSIFI pairs. The average portfolio similarity across illiquid and downgraded securities is much larger for PSIFI pairs (0.74 and 0.41, respectively) than for non-PSIFI pairs (0.42 and 0.07, respectively). To the extent that common holdings of illiquid and downgraded securities are more likely to result in common sales that impact prices, this finding provides support to FSOC's concern over the portfolio composition of large insurers.

To determine which insurers sell similar asset classes or issuers, we construct a measure of common sales. For each insurer, we create a vector of quarterly non-negative net sales (sales minus purchases) of each asset class or security issuer. We then calculate the common selling of insurers i and j as the dot product of the pair of insurers' quarterly net sales vectors. That is,

$$Common\ Sales_{ijt} = \mathbf{Net\ Sales}_{it} \cdot \mathbf{Net\ Sales}_{jt} \tag{3}$$

where $Net\ Sales_{it}$ is insurer i's and $Net\ Sales_{jt}$ is insurer j's vector of non-negative net sales in quarter t. Depending on whether asset class or issuer net sales are used, we refer to this quantity as common sales at the asset class (*Common Sales_AC*) or issuer (*Common Sales_I*) level. It is important to note that our measure of common sales is based on dollar amounts that are not normalized by total holdings or sales. This allows us to focus on large common sales that are most likely to generate a price impact.[12] Because we are interested in the determinants of common net sales, for each pair in each quarter we only calculate common sales if both insurers have positive net sales.

Figure 6 presents the quarterly time-series average of $Ln(1 + Common\, Sales)$ at the asset class and issuer level for the sample of all insurers and for the subsamples of PSIFI and non-PSIFI pairs. The figure shows that most common selling by insurers is done in the last quarter of the year, so in our multivariate analysis we use year-quarter fixed effects to control for this pattern. As with portfolio similarity, PSIFI insurer pairs have greater common sales than non-PSIFIs. Interestingly, we do not see an increase in common selling, whether at the asset class or issuer level, during or around the recent financial crisis.

Table 2 provides additional summary statistics on common sales. In the sample of all insurer pairs the average of $Ln(1 + Common\, Sales\_AC)$ is almost 15 and that of $Ln(1 + Common\, Sales\_I)$ is 6. PSIFI pairs tend to sell more in common both at the asset class (34.42) and issuer (31.89) level compared to non-PSIFI pairs (14.27, and 5.38, respectively). This larger magnitude is not surprising, since PSIFIs have larger portfolios and common sales are not normalized.

4 Determinants of Portfolio Similarity

To gain a better understanding of the determinants of pairwise portfolio similarity, we examine its correlation with different insurer characteristics. Because our dependent variable is a pairwise variable, we construct our independent variables in a similar fashion. To capture a pair's business-line similarity, we use indicator variables that equal 1 if both insurers in a pair are life insurers (*Life_Pair*) or P&C insurers (*PC_Pair*), and 0 otherwise. For each pair of insurers, we consider their joint size by using the natural logarithm of the dot product of their holdings' dollar value (*Prod_Size*). We also measure the insurer pair's joint portfolio concentration as the dot product of their portfolio concentrations at either the asset class (*Prod_Conc_AC*) or issuer (*Prod_Conc_I*) level.

Table 3 presents the results from estimating OLS regressions, in which the dependent variable

[12] Our results are robust to using the cosine similarity of quarterly net sales instead of the dollar amount of common sales. Cosine similarity of quarterly net sales is calculated analogously to portfolio similarity and is measured as the dot product of a pair's sale weight vectors normalized by the vectors' lengths. The limitation of this method is that it cannot capture the joint magnitude of selling, which may be of interest to regulators.

is pairwise portfolio similarity at the asset class level in columns (1)–(3), or issuer level in columns (4)–(6). In columns (1)–(3), we find that *Similarity_AC* between two insurers is greater if they are both life or both P&C insurers, regardless of whether we examine all, PSIFI or non-PSIFI pairs. This finding is intuitive because insurers likely make asset allocation decisions with their liabilities in mind. Since insurers in the same line of business have similar liabilities, we would expect them to have similar assets as well.

Analyzing portfolio similarity at the issuer level in column (4), we find somewhat different results from those at the asset class level. For the sample of all insurers, a P&C pair has more similar holdings but a life pair does not. When we examine PSIFI and non-PSIFI pairs separately in columns (5)–(6), we find that this result is limited to non-PSIFI life pairs. PSIFI pairs have greater portfolio similarity when they are both in the same line of business, whether life or P&C.

Regardless of whether we measure portfolio similarity at the asset class or issuer level, it is always greater if both insurers have the same PSIFI classification. Specifically, when insurers in a pair are either both PSIFI or both non-PSIFI, they have larger portfolio similarity compared to pairs where one insurer is a PSIFI and another is not. Moreover, among non-PSIFI insurers, larger insurer pairs have more similar portfolios as indicated by the positive coefficient on *Prod_Size*.[13] One interpretation of the relationship between insurer size and portfolio similarity, is that larger insurers may invest in similar assets because of the scarcity of unique investments at a particular size threshold.

We do not find consistent results with respect to the relationship between a pair's portfolio similarity and portfolio concentration. When measured at the asset class level, concentration tends to be negatively related to portfolio similarity. At the issuer level, this relationship reverses for insurers other than PSIFIs. Non-PSIFI pairs tend to have greater portfolio similarity if they are more concentrated at the issuer class level (columns (4) and (5) in Table 3). This may be due to the propensity of small insurers to invest in well-known issuers, and to draw from the same pool of advisors for their portfolio construction.

[13]This finding is similar if instead of the continuous variable *Prod_Size* we instead use indicator variables for size similarity. These indicator variables equal 1 if we characterize non-PSIFI pairs as either large or small based on whether both insurers in a pair have total assets above or below the median for the sample.

5 Portfolio Similarity and Common Sales

5.1 Baseline Analysis

The FSOC argues that insurers with more similar holdings are likely to have more similar sales, thus exacerbating the price impact of each individual sale and potentially disrupting markets. Common selling can occur if insurers, which are invested in similar assets, sell a pro rata share of their portfolio or if certain characteristics of the assets make them more likely to be sold (e.g., liquidity or credit quality). However, a positive relationship between portfolio similarity and subsequent common sales is not a foregone conclusion. Recognizing the potential for disruption in financial markets and losses to their portfolios due to price impact, insurers may approach asset liquidation decisions strategically to minimize the likelihood of common selling and avoid downward pressure on prices. If this is the case, portfolio similarity may not be related to common sales.

To ascertain whether there is a link between similar holdings and similar sales, we use portfolio similarity to explain both (i) the probability and (ii) magnitude of common sales. For the former, we estimate a probit model in which the dependent variable is an indicator variable that equals 1 if *Common Sales* > 0, and 0 otherwise. For the latter, we estimate a tobit model because, as shown in Table 2, the dependent variable *Common Sales* equals 0 for many insurer pairs other than PSIFIs.

The estimation results are presented in Table 4 and indicate a strong positive relationship between portfolio similarity, and the probability and magnitude of common sales. The coefficients on *Similarity_AC* and *Similarity_I* are positive and significant in columns (1)–(6). That is, pairs of insurers that have more similar holdings are more likely to sell similar asset classes and issuers. The relationship is present even after controlling for other pair characteristics that may affect common selling, and in both PSIFI and non-PSIFI subsamples.

We also document that common sales are related to a pair's business line similarity, joint size, and joint portfolio concentration, holding portfolio similarity constant. For example, if both insurers in a pair are P&C insurers, the pair has greater common sales at both the asset class and issuer levels. The effect of business line similarity reverses for life pairs, which have lower common sales. The different results for P&C and life pairs may be due to life and P&C insurers having different investment horizons. Life insurers are more likely to be long-term investors while P&C insurers are more likely to experience stochastic shocks to liabilities that necessitate asset liquidation.

We find that insurer size is related to common sales. For example, pairs of PSIFI insurers have greater common sales than other insurers. Although non-PSIFIs have lower common sales than PSIFIs, among them, larger pairs have larger common sales as shown in columns (4) and (8). Thus, our findings support FSOC's use of firm size as one criteria for non-bank SIFI designation, but also suggest that the $50 billion size threshold does not appear to be particularly meaningful.

We also document that the joint portfolio concentration of a pair, either at the asset class or issuer level, leads to a decrease in both the probability and magnitude of common sales. The negative coefficient on *Prod_Conc* indicates that the more diversified a pair's holdings, the more likely and the greater its common sales. This finding is consistent with a number of papers, which have suggested that portfolio diversification increases the potential for common selling that may lead to financial instability (Haldane and May (2011), Gai et al. (2011), and Allen et al. (2012)).

The results presented in this section confirm FSOC's concern that portfolio similarity is an important determinant of common sales. Thus, our measure could be used to monitor insurers and identify those insurers that may contribute more to the asset liquidation channel of systemic risk transmission.

5.2 Return Covariance and Common Sales

We next examine whether a pair's stock return covariance contains the same information about common sales as our measure of portfolio similarity. Prior studies have proposed the use of market-based measures to quantify the interconnectedness of financial institutions. Specifically, Billio et al. (2012), Neale et al. (2012), and Brunetti et al. (2018) argue that return covariance captures, at the aggregate level, the on- and off-balance-sheet links between and within the insurance and banking industries. However, this and other market-based measures of interconnectedness cannot be constructed for many financial institutions that are not publicly-traded (e.g. hedge funds, and private banks and insurers) but may contribute to the asset liquidation channel of risk transmission. Since some of these institutions report portfolio holdings, our similarity measure may be a useful metric for forecasting these institutions' potential for common selling.

In order to determine whether a pair's covariance of stock returns (*RetCov_Pair*) is a good proxy for portfolio similarity when it comes to predicting common sales, we first use it instead of portfolio similarity in our base specification. The estimation results at the asset class and issuer level in columns (1) and (5) of Table 5, respectively, indicate no evidence of a relationship between *RetCov_Pair* and common sales. When a pair's portfolio similarity is included in the remaining specifications alongside return covariance, the relationship between portfolio similarity and common sales remains positive and significant, while that between return covariance and common sales is either negative or insignificant. Thus, we conclude that an insurer pair's return covariance is not a substitute for portfolio similarity when it comes to predicting the pair's common selling. This is likely due to the fact that return covariance reflects many different aspects of a pair's interconnectedness in addition to similarity in portfolio allocation.

5.3 Asset Liquidity and Issuer Downgrades

Since prior studies document that individual insurers sell liquid (Ellul et al. (2015)) and downgraded (Ellul et al. (2011)) assets when they need to replenish regulatory capital, we explore whether the relationship between portfolio similarity and common sales is due to insurers' common holdings of these types of assets. Specifically, we decompose the portfolio similarity between a pair of insurers by recomputing the cosine similarity using only liquid (*Similarity_AC_Liquid*) or illiquid (*Similarity_AC_Illiquid*) asset classes, and downgraded (*Similarity_I_Downgraded*) or not downgraded (*Similarity_I_NotDowngraded*) issuers. Cont and Schaanning (2018) propose a measure that captures liquidity-weighted overlap between banks' portfolios, and show they are related to fire sale losses. We then regress common sales on the decomposed portfolio similarity measures.

Table 6 presents the estimation results, and indicates that the positive relationship between portfolio similarity and common sales is not driven by the liquidity or credit quality of insurers' common holdings. In all specifications, the coefficient on each of the decomposed portfolio similarities – liquid, illiquid, downgraded, and not downgraded – is highly significant and positive. Thus, common sales are larger regardless of whether insurers hold more similar liquid or illiquid asset classes, and more similar downgraded or not downgraded issuers.

5.4 Regulatory Capital Constraints

The literature has documented that firms subject to capital requirements liquidate assets quickly when their regulatory capital is depleted. These regulation-induced fire sales can have a disruptive effect on markets by putting downward pressure on prices (Ellul et al. (2011) and Merrill et al. (2013)). The effect of fire sales may be magnified to the extent that insurers with low regulatory capital and similar holdings liquidate more of these holdings. In this section, we examine whether the relationship between portfolio similarity and common sales is stronger for capital constrained insurers.

We assess the extent to which an insurer is regulatory capital constrained through its ratio of statutory to risk-based capital (RBC ratio). A large RBC ratio can potentially reduce the need to liquidate assets and can provide a buffer against a shock to an insurer's balance sheet. To allow for non-linearity in the relationship between RBC and common sales, we consider both the level of RBC and whether RBC is relatively low. Thus, our set of independent variables includes both the natural logarithm of the product of RBC for an insurer pair ($Prod\_RBC$), and a pairwise indicator variable (RBC_Low_Pair) equal to 1 if both insurers' RBC ratios are at or below the bottom quartile of the sample and to 0 otherwise.[14] If the effect of portfolio similarity on a pair's common selling is more pronounced when both insurers in the pair are capital constrained, then the interaction term $Similarity * RBC\_Low\_Pair$ should be positively related to common sales.

Table 7 presents our analysis on the magnifying effect of regulatory capital constraints. We confirm the literature's findings that insurers with lower capital are more likely to sell securities in common. The coefficient of $Prod\_RBC$ is significantly negative, and the coefficient of RBC_Low_Pair is significantly positive, for the sample as a whole in columns (1) and (4) and for non-PSIFI pairs in columns (3) and (6). Moreover, the effect of capital constraints is magnified when portfolio similarity is taken into consideration as the coefficient on $Similarity * RBC\_Low\_Pair$ is positive and significant. We find evidence that at the asset class level capital constrained pairs with more similar portfolios have even larger common sales than non-constrained pairs. We do not find a similar magnifying effect at the issuer level.[15]

[14]Our results are robust to using the median RBC as the cutoff.

[15]We do not find evidence that RBC affects the size of the common sales for PSIFI pairs (columns (2) and (5)). This is maybe because large insurers tend to be very well-capitalized and thus, their selling behavior is unlikely to be affected by regulatory capital. (Indeed, RBC_Low_Pair=1 for only 36 PSIFI pair-years out of 23,692 in our sample.)

6 Liquidity Shocks and Price Impact

In this section, we investigate whether our finding that insurers with more similar portfolios have larger common sales persists in the context of potential forced sales and whether portfolio similarity can predict the magnitude of the price impact on insurers' bond portfolios. We do so by examining two shocks to insurers' liquidity needs. The first is the bankruptcy of Lehman in the third and fourth quarters of 2008 and the second is Hurricanes Katrina and Rita, which made landfall in Florida on August 25, 2005, and Louisiana on September 24, 2005, respectively.

6.1 Lehman's Failure

Lehman's failure was one of several events to impact the financial markets in September 2008 and was the largest bankruptcy filing in U.S. history. According to Shleifer and Vishny (2011), "with natural buyers of distressed securities sidelined after Lehman, security prices went into a free fall" and "liquidity problems caused by fire sales were indeed severe after Lehman." Therefore, there is the potential for fire sale spillover from Lehman's failure (and the banking industry, more generally) to the insurance industry. We examine the impact of insurers' exposure the banking sector during this event to see how shocks may propagate through the insurance industry. To capture the time period surrounding the bankruptcy, we create a variable, *Lehman*, that is an indicator variable equal to 1 in the third and fourth quarters of 2008, 0 otherwise.

Ideally, we would like to measure the cosine similarity of bank and insurer bond holdings to gauge whether potential fire sales are related to the extent that the portfolios of the two types of firms are similar. Unfortunately, such granular data is not available. Therefore, given the stress on bank balance sheets during this time period, we measure insurer pairs' exposure to the banking sector by the amount of bank debt they jointly hold. We define *Exposed* as an indicator variable equal to 1 if both insurers' portfolio holdings (in dollars) of financial firm corporate debt securities relative to total corporate debt securities' held is at or above the 75th percentile of the sample in that year, 0 otherwise.

Around the same time as the Lehman failure, AIG's exposure to credit default swaps was the catalyst to a downgrade in its credit rating, creating a collateral shortfall that eventually lead to its near collapse and bail out by the federal government. Arguably, the collapse of AIG was the result of its exposure to the banking sector's mortgage activity and therefore, may act as a proxy for the exposure to a banking crisis for the insurance industry. We define *Exposed* an indicator variable equal to 1 if both insurers' portfolio similarity with AIG at the issuer level is above the median level in that year, 0 otherwise. If portfolio similarity can predict forced selling in common, exposed insurers with more similar portfolios will have larger common sales during the last two quarters of 2008. That is, for both types of exposure, bank debt and AIG, we hypothesize that the effect of the triple interaction *Similarity_I*Lehman*Exposed* on common sales should be positive and significant.[16]

Panel (a) of Table 8 presents the results of a Tobit estimation on the effect of exposure to bank debt or similarity to AIG on common sales. The effect of exposure to bank debt for all insurer pairs is reported in columns (1) and (2) and the effect of similarity to AIG's portfolio in columns (3) and (4). We use the full sample and a subsample of only those pairs that have exposure to bank debt. The triple interaction term, *Similarity_I*Lehman*Exposed*, for the sample of all pairs is statistically significant and indicates that insurer pairs with greater portfolio similarity and higher exposure to bank debt, have greater common selling during the two quarters surrounding the Lehman failure. When we restrict the sample to only those insurer pairs that are defined as exposed, we find some evidence that the interaction term *Similarity_I*Lehman* is significant and positive. We find a similar relationship on common sales for exposure to AIG in columns (3) and (4). The more similar an insurer pair's portfolio is to AIG and to each other, the greater are the common sales during 2008Q2 and 2008Q4. This relationship remains strong even when examining only those insurer pairs that have high exposure to AIG in column (4).

The effect of portfolio similarity on common sales is only relevant if it can contribute to price impact in times of financial instability. Specifically, we investigate whether assets held by insurer pairs with greater portfolio similarity experience a larger drop in value around the time of the Lehman failure. Our approach is similar to that of Manconi et al. (2012) who examine whether the exposure of institutional investors to securitized bonds before the onset of the financial crisis, increases yield spreads more during the crisis. Since we are interested in measuring the price impact on illiquid assets, and because fixed-income pricing data is only available for corporate bonds, the

[16]We limit our analysis to insurer pairs that sell at least one issuer in common during the two quarters.portfolio similarity at the issuer level and to be consistent with the next section, we focus on a single primary asset class, corporate bonds.

analysis in this section is limited to corporate bonds.

To match the pairwise nature of our portfolio similarity measure, we similarly construct a pairwise measure of the change in asset prices. Specifically, for each pair of insurers i and j, $\Delta YS_{i,j}$ is the change in the yield spread of the pair's joint corporate bond portfolio (prior to Lehman's bankruptcy filing) from 2008Q4 (after the Lehman's bankruptcy filing). To construct this measure, we start with all bonds in the TRACE Enhanced database for which a yield to maturity is available at the end of 2008Q2 and 2008Q4. For each bond, we calculate the yield spread as the difference between the bond's yield to maturity from TRACE Enhanced and the yield to maturity on a maturity-matched Treasury bond from the H.15. Federal Reserve Release.[17] The yield spread change is a bond's yield spread at the end of 2008Q4 minus the yield spread at the end of 2008Q2. We construct each insurer's portfolio yield spread change as the weighted average yield spread change of the corporate bonds in its portfolio. That is,

$$\Delta YS_i = \sum_{k=1}^{K} w_{ik} \Delta BondYS_{ik} \tag{4}$$

where ΔYS_i is the portfolio yield spread change of insurer i from 2008Q2 to 2008Q4, $\Delta BondYS_{ik}$ is the yield spread change of bond k in its portfolio over the same time period, K is the number of sample bonds held by insurer i at the end of 2007, and w_{ik} is the weight of bond k in its portfolio, using the par value held at the end of 2007 as the weight. We then construct an insurer pair's joint portfolio yield spread change as the weighted average of each insurer's portfolio yield spread change, using the par value of the bonds held by each insurer as the weight. Specifically,

$$\Delta YS_{ij} = w_i \Delta YS_i + w_j \Delta YS_j \tag{5}$$

where ΔYS_{ij} is the joint portfolio's yield spread change for the pair of insurers i and j from 2008Q2 to 2008Q4.

Given our previous findings, we expect that when faced with a liquidity shock, insurers with more similar portfolios will experience a larger drop in the price (or increase in yield) of their corporate

[17] We clean the data for cancellations, corrections, reversals and duplicate interdealer trade reporting following Dick-Nielsen (2014). We further exclude when-issued, locked-in, commission, and special-price-condition trades as well as trades that settle in more than 3 days. On each day, a bond's yield is the trade-size weighted average of yields throughout the day.

bond holdings than other insurers. That is, we hypothesize that the relationship between a pair's joint portfolio yield spread change and the interaction term *Similarity_I*Exposed* will be positive and significant. Our specification also includes as controls the weighted average characteristics of the bonds held by the insurer pair measured on the last trade date in the quarter prior to the Lehman collapse. These include the weighted average number of trades in the two quarters prior to the failure (*Avg. Ln(Trades)*), the weighted average natural logarithm of the bonds' issuance amount (*Avg. Ln(Amount)*), and the weighted average natural logarithm of the bond's years to maturity (*Avg. Ln(Maturity)*). We also control for insurer pair characteristics: joint size, portfolio concentration, and regulatory capital.

The estimation results are presented in Panel (b) Table 8 for insurer pairs that differ on their exposure to the debt of the banking sector and to AIG. In columns (1) and (3), we find that the coefficient on the interaction term *Similarity_I*Exposed* is positive and significant. This indicates that exposed pairs either with bank debt or AIG with more similar portfolios experience a larger increase in their joint portfolio's yield spread around the time of the Lehman bankruptcy compared to other pairs and other time periods. When examining only the sample of exposed insurers in columns (2) and (4), we find that the increase in joint portfolio bond yield spread is greater, the more similar the pair's portfolios.[18]

6.2 Hurricane Exposure

In this section, we examine an exogenous shock to P&C insurers' liabilities and the effect of portfolio similarity on common sales and price impact. According to the National Oceanic and Atmospheric Administration, total damages from the hurricanes were $160 billion. The impact on P&C insurers was particularly severe with $41 billion of filed claims on personal property, vehicle, and business policies.[19] Since the large number of claims most likely necessitated the sale of securities to cover losses, we use this natural disaster as a shock to the liquidity needs of P&C insurers with significant exposure in the hurricane-affected states.[20] This empirical setup allows

[18]The correlation between insurer pair's designation as exposed to the banking sector and to AIG is negative (-0.15) and fairly low. Thus, this analysis is not capturing the same economic exposure.

[19]See the Insurance Information Institute publication "Infographic: Hurricane Katrina 10 Years Later" at https://www.iii.org/article/infographic-hurricane-katrina-10-years-later.

[20]Although 1,833 lives were lost during the storm, many of them were uninsured. Therefore, life insurers were relatively unaffected by the hurricanes and are thus excluded from the analysis. See Towers Watson, "Hurricane Katrina: Analysis of the Impact on the Insurance Industry" at https://biotech.law.lsu.edu/blog/impact-of-hurricane-

us to minimize the incidence of regular portfolio rebalancing and of selling motivated by changing issuer fundamentals, to isolate the effect of portfolio similarity on forced common sales and the resultant effect on prices.[21]

We collect data for each P&C insurer on the amount of premiums written in the two states most affected by Hurricanes Katrina and Rita: Louisiana and Mississippi.[22] We define a pair of insurers as being exposed to potential losses from these hurricanes, *Exposed*, if both insurers' premiums written in hurricane-affected states relative to total premiums written in each year, are in the top quartile of the sample. We create an indicator variable, *Hurricane,* equal to 1 in 2005Q3, and 0 otherwise.

The estimation results are presented in Panel (a) Table 9 and provide evidence consistent with our hypothesis. The coefficient on *Similarity_I*Hurricane*Exposed* is positive and significant in columns (1) and (2). Column (1) includes all insurer pairs and column (2) excludes mixed pairs, i.e., pairs of an exposed and a non-exposed insurers. When we limit our sample to just exposed insurers in column (3), we find that their portfolio similarity results in larger common sales during the quarter of the hurricanes than during any other quarter.

The results in Table 9 also indicate that during the quarter of the hurricanes exposed insurers sell more in common regardless of portfolio similarity, consistent with Manconi et al. (2016). The coefficient on *Hurricane*Exposed* in both columns (1) and (2) is positive and significant. In contrast, the negative coefficient on *Hurricane* in these columns implies that insurers without a significant exposure in hurricane-affected states sell less in common. This could be because non-exposed insurers attempt to avoid common sales at a time when markets are being negatively affected by the selling behavior of exposed insurers. We also document that *Similarity_I* is positive and significant in all columns, which reiterates our earlier conclusion that greater portfolio similarity always results in larger common sales.

Next, we investigate whether assets held by insurer pairs with greater portfolio similarity experience a larger drop in value around the time of Hurricanes Katrina and Rita using a similar

katrina-on-the-insurance-industry-towers-watson.pdf.

[21]The occurrence of Hurricane Katrina has been used in several recent studies. Manconi et al. (2016) exploit the impact of the hurricane on insurers' corporate bond sales to examine the drop in bondholder concentration. Liu (2016) finds that insurers without hurricane exposure exploit the discounted prices after disasters to realize significant profits. Finally, Chaderina et al. (2018) show that insurers are more likely to fire sell liquid assets when faced with an exogenous liquidity shock.

[22]Although several states were affected, the majority (93%) of insured losses occurred in Louisiana and Mississippi.

approach as the prior subsection on the Lehman failure. The dependent variable is a pair's joint portfolio yield spread change from 2005Q2 (prior to Hurricanes Katrina and Rita) to 2005Q4 (after the hurricanes), defined as the weighted average of the insurers in the pair's portfolio yield spread change, using the par value of the bonds held by each insurer at the end of 2004 as the weight. An insurer's portfolio yield spread change is the weighted average yield spread change of the corporate bonds in its portfolio, using each bond's par value held at the end of 2004 as the weight. The yield spread change of a bond is its yield spread at the end of 2005Q4 minus the yield spread at the end of 2005Q2, where a yield spread is the bond's yield to maturity minus that on a maturity-matched Treasury.

The estimation results are presented in Panel (b) Table 9. In columns (1) and (2), we find that the coefficient on the interaction term *Similarity_I*Exposed* is positive and significant. This indicates that exposed pairs with more similar portfolios experience a larger increase in their joint portfolio's yield spread around the time of the hurricanes compared to other pairs. When examining only the sample of exposed insurers in column (3), we find that the increase in joint portfolio bond yield spread is greater, the more similar the pair's portfolios. Overall, the findings in this section provide evidence that the relationship between portfolio similarity and common sales has the potential to depress prices and affect the value of insurers' holdings.

7 Individual Insurer Portfolio Similarity

In the previous sections, we provide strong evidence that pairwise portfolio similarity can predict an insurer pair's common sales and price impact. But in order for regulators to engage in the prudential supervision of insurers, they must be able to identify specific entities that may contribute to the asset liquidation channel of risk transmission. In this section, we propose a methodology that transforms the portfolio similarity of insurer pairs into a metric at the individual insurer level by averaging an insurer's portfolio similarity with all others in the industry. Specifically, for insurer i at year-end t,

$$Similarity\_Avg_{it} = \frac{\sum_{j \neq i, j=1}^{J} Similarity_{ijt}}{J-1} \tag{6}$$

where J is the number of insurers. Depending on whether we use asset class or issuer pairwise portfolio similarity, we refer to this measure as average portfolio similarity at the asset class

($Similarity\_Avg\_AC$) or issuer ($Similarity\_Avg\_I$) level.

We hypothesize that an insurer with higher average portfolio similarity will sell more in common with other insurers. To test this hypothesis, we construct a measure of common sales at the individual insurer level as the sum of all its pairwise common sales with the other insurers in the sample. That is, for insurer i in quarter t,

$$Common\ Sales\_Aggr_{i,t} = \sum_{j \neq i, j=1}^{J} Common\ Sales_{i,j,t} \tag{7}$$

Analogously to average portfolio similarity, aggregate common sales are constructed at the asset class ($Common\ Sales\_Aggr\_AC$) or issuer ($Common\ Sales\_Aggr\_I$) level. We then regress this insurer-level measure of aggregate common sales on the insurer's prior year average portfolio similarity at the asset class or issuer level.[23] We also control for the insurer's size ($Size$), concentration of holdings ($Conc\_AC$ or $Conc\_I$), and line of business (PC and $Life$ indicators).

The results are presented in Table 10 and indicate that an insurer's *Similarity_Avg* is strongly related to its subsequent aggregate common sales even after controlling for the size of the insurer.[24] In other words, the more similar the portfolio holdings of a specific insurer to those of other insurers, the more that insurer contributes to common selling in the aggregate.

Overall, the results in this section suggest that the average portfolio similarity of an insurer conveys useful information about its common sales with other insurers even after controlling for other insurer characteristics such as size, total sales, concentration, and business line. Thus, such a measure could be used by regulators to identify systemically important insurers that are most likely to contribute to asset liquidation vulnerabilities.

8 Conclusion

Recent designations of insurers as systemically important presuppose that insurers holding similar assets have large common sales that could impact prices. We provide evidence consistent with this presumption.

First, we document that insurers' portfolios are indeed very similar. Using cluster analysis,

[23] Our results on average portfolio similarity remain robust if we use the average of the insurer's common sales.
[24] Our results are robust to using total net sales instead of size.

we find that insurers follow a small number of investment strategies and that these strategies are relatively stable through time. Furthermore, in support of FSOC's particular concern over large insurers, we document that insurers that could be designated as SIFIs based on their size have higher average portfolio similarity than other insurers.

Second, we develop a novel measure of pairwise interconnectedness that focuses on insurers' portfolio similarity. We examine the measure's association with common selling and find that pairs of insurers that have greater portfolio similarity have larger subsequent common sales. This result holds across all insurer pairs regardless of potential SIFI status. We show that our measure of portfolio similarity predicts common selling even after incorporating a market measure of interconnectedness - stock return covariance - and considering the liquidity and credit quality of the portfolio. Furthermore, for certain insurers, regulatory capital constraints and periods of market stress magnify the relationship between portfolio similarity and common selling.

Third, we exploit the occurrence of the Lehman failure and Hurricanes Katrina and Rita to isolate the incidence of forced sales as opposed to anticipated portfolio rebalancing or trading motivated by changing security fundamentals. We find that in response to these liquidity shocks, insurers with large exposures to the banking sector, AIG, or hurricane-affected states have even greater common sales when they have greater portfolio similarity. Using corporate bond price information, we also show that these insurers' holdings experience a drop in value from the quarter before to the quarter after Lehman and the hurricanes and that this drop is larger when exposed insurers have more similar portfolios.

Finally, we use the average portfolio similarity of an individual insurer with all others in the industry as a way to gauge its potential to contribute to financial instability. We show that while insurer characteristics affect an insurer's aggregate common sales, its average portfolio similarity remains a significant predictor.

Overall, our results indicate that commonality in asset holdings captures important mechanics of the asset liquidation channel of risk transmission in the insurance industry. Specifically, the portfolio similarity measure we develop can predict the probability and magnitude of common selling of similar asset classes and similar issuers that may negatively affect prices. Furthermore, our measure captures similarity across the entirety of financial institutions' portfolios and does not require that institutions have publicly traded equity. Thus, we believe that our portfolio similarity measure can be used by regulators to predict the common selling of any institution that reports security or asset class level holdings.

References

Allen, F., Babus, A., Carletti, E., 2012. Asset commonality, debt maturity and systemic risk. Journal of Financial Economics 104, 519–534.

Billio, M., Getmansky, M., Lo, A. W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics 104, 535–559.

BIS, 2014. The G-SIB assessment methodology - score calculation, working paper available at http://www.bis.org/bcbs/publ/d296.htm.

Brunetti, C., Harris, J. H., Mankad, S., Michailidis, G., 2018. Interconnectedness in the interbank market. Journal of Financial Economics F.

Castiglionesi, F., Navarro, N., 2008. Optimal fragile financial networks, working paper available at http://ssrn.com/abstract=1089357.

Chaderina, M., Muermann, A., Scheuch, C., 2018. The dark side of liquid bonds in fire sales, working paper available at https://ssrn.com/abstract=2995544.

Chiang, C.-C., Niehaus, G., 2016. Investment herding by life insurers and its impact on bond prices, working paper available from authors.

Cont, R., Schaanning, E., 2018. Monitoring indirect contagion.

Cont, R., Wagalath, L., 2016. Institutional investors and the dependence structure of asset returns. International Journal of Theoretical and Applied Finance 19, 10–47.

Cummins, J. D., Weiss, M. A., 2014. Systemic risk and the U.S. insurance sector. Journal of Risk and Insurance 81, 489–528.

Dick-Nielsen, J., 2014. How to clean Enhanced TRACE data, working paper available at https://ssrn.com/abstract=2337908.

Dunn, J. C., 1974. Well-separated clusters and optimal fuzzy partitions. Journal of Cybernetics 4, 95–104.

Ellul, A., Jotikasthira, C., Lundblad, C. T., 2011. Regulatory pressure and fire sales in the corporate bond market. Journal of Financial Economics 101, 596–620.

Ellul, A., Jotikasthira, C., Lundblad, C. T., Wang, Y., 2015. Is historical cost accounting a panacea? Market stress, incentive distortions, and gains trading. Journal of Finance 70, 2489–2538.

Fang Cai, Han, S., Li, D., Li, Y., 2018. Institutional herding and its price impact: Evidence from the corporate bond market, forthcoming *Journal of Financial Economics*.

FSOC, 2013. Basis for the Financial Stability Oversight Council's final determination regarding Prudential Financial, Inc., available at https://www.treasury.gov/initiatives/fsoc/designations.

Gai, P., Haldane, A., Kapadia, S., 2011. Complexity, concentration and contagion. Journal of Monetary Economics 58, 453–470.

Geneva Association, T., 2010. Systemic risk in insurance: An analysis of insurance and financial stability. Special Report of the Geneva Association Systemic Risk Working Group .

Grace, M. F., 2010. The insurance industry and systemic risk: Evidence and discussion, working paper available at https://ssrn.com/abstract=1593645.

Haldane, A. G., May, R. M., 2011. Systemic risk in banking ecosystems. Nature 469, 351–355.

Handl, J., Knowles, J., Kell, D. B., 2005. Computational cluster validation in post-genomic data analysis. Bioinformatics 21, 3201–3212.

Hanley, K. W., Hoberg, G., 2010. The information content of IPO prospectuses. Review of Financial Studies 23, 2821–2864.

Hanley, K. W., Hoberg, G., 2012. Litigation risk, strategic disclosure and the underpricing of initial public offerings. Journal of Financial Economics 103, 235–254.

Hanley, K. W., Nikolova, S., 2017. Rethinking the use of credit ratings in capital regulation, working paper available at http://ssrn.com/abstract=2357145.

Harrington, S. E., 2009. The financial crisis, systemic risk, and the future of insurance regulation. Journal of Risk and Insurance 76, 785–819.

Ibragimov, R., Jaffee, D., Walden, J., 2011. Diversification disasters. Journal of Financial Economics 99, 333 –348.

Jian Cai, Eidam, F., Saunders, A., Steffen, S., 2018. Syndication, interconnectedness, and systemic risk. Journal of Financial Stability 34, 105–120.

Kartasheva, A., 2014. Insurance in the financial system, bIS working paper.

Koijen, R. S. J., Yogo, M., 2016. Shadow insurance. Econometrica 84, 1265–1287.

Liu, M., 2016. Strategic liquidity hoarding and predatory trading: An empirical investigation, u.

MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations. Proceedings of the fifth Berkeley symposium on mathematical statistics and probability 1, 281–297.

Manconi, A., Massa, M., Yasuda, A., 2012. The role of institutional investors in propagating the crisis of 2007-2008. Journal of Financial Economics 104, 491–518.

Manconi, A., Massa, M., Zhang, L., 2016. Bondholder concentration and credit risk: Evidence from a natural experiment. Review of Finance 20, 127–159.

Merrill, C. B., Nadauld, T., Stulz, R. M., Sherlund, S. M., 2013. Why were there fire sales of mortgage-backed securities by financial institutions during the financial crisis?, working paper available at http://ssrn.com/abstract=2212684.

Nanda, V., Wu, W., Zhou, Z., 2017. Insurer investment commonality: Fire sale risk and corporate yield spreads, working paper.

Neale, F. R., Drake, P. P., Schorno, P., Semann, E., 2012. Insurance and interconnectedness in the financial services industry, working paper.

Rousseeuw, P. J., 1987. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. Journal of Computational and Applied Mathematics 20, 53–65.

Shleifer, A., Vishny, R., 2011. Fire sales in finance and macroeconomics. Journal of Economic Perspectives 25, 29–48.

Sias, R., Turtle, J., Zykaj, B., 2016. Hedge fund crowds and mispricing. Management Science 62, 764–784.

Wagner, W., 2010. Diversification at financial institutions and systemic crises. Journal of Financial Intermediation 19, 373 –386.

Wagner, W., 2011. Systemic liquidation risk and the diversity diversification trade-off. The Journal of Finance 66, 1141–1175.

Appendix A: Asset Classes

Asset-backed securities (other than CMBS and RMBS)
Commercial mortgage-backed securities (CMBS)
Corporate bonds: Banks
Corporate bonds: Basic materials, durables, cyclicals
Corporate bonds: Consumer staples, retail
Corporate bonds: Energy
Corporate bonds: Financials not further defined
Corporate bonds: Health
Corporate bonds: Insurers
Corporate bonds: Not further defined
Corporate bonds: Pharmaceutical, chemical
Corporate bonds: Services
Corporate bonds: Technology
Corporate bonds: Utilities
Equity: Banks
Equity: Basic materials, durables, cyclicals
Equity: Consumer staples, retail
Equity: Energy
Equity: Financials not further defined
Equity: Government-sponsored entity
Equity: Health
Equity: Insurers
Equity: Not further defined
Equity: Pharmaceutical, chemical
Equity: Services
Equity: Technology
Equity: Utilities
Government-sponsored entity debt securities
Municipal bonds: General obligation
Municipal bonds: Revenue and other non-general obligation
Mutual fund shares
Residential mortgage-backed securities (RMBS)
Sovereign bonds
U.S. government securities (including securities issued by all federal agencies)

Appendix B: Variable Definitions

Variable	Definition
Avg. Ln(Amt)	Weighted average of the natural logarithm of the issuance amount of the corporate bonds held by a pair.
Avg. Ln(Mat)	Weighted average of the natural logarithm of the years to maturity of the corporate bonds held by a pair.
Avg. Ln(Trades)	Weighted average of the natural logarithm of the 2005Q1–2005Q2 number of trades of the corporate bonds held by a pair.
Common Sales_Aggr_AC or Common Sales_Aggr_I	The sum of an insurer's common sales with all other insurers, at the asset class (AC) or issuer (I) level.
Common Sales_AC or Common Sales_I	The dot product of an insurer pair's net dollar sales vectors at the asset class (AC) or issuer (I) level.
Conc_AC or Conc_I	Asset class (AC) or issuer(I) level Herfindahl index of an insurer's portfolio: $Conc_{it} = \sum_{k=1}^{K} w_{itk}^2$ where w_{itk} is asset class/issuer k's proportion in insurer i's portfolio at the end of year t. Asset class/issuer level proportions are calculated as the dollar amount invested in each asset class/issuer relative to the total value of the insurer portfolio.
Crisis	An indicator variable equal to 1 for the years 2007, 2008, and 2009; 0 otherwise.
Exposed	An indicator variable equal to 1 if the annual proportion of Louisiana and Mississippi premiums written to total premiums written is in the top quartile of the sample for both insurers in a pair, 0 otherwise.
Hurricane	An indicator variable equal to 1 in 2005Q3, 0 otherwise.
Joint portfolio yield spread change	Weighted average of a pair's portfolio yield spread changes, using 2004 corporate bond par value held as the weight. Portfolio yield spread change is the weighted average of an insurer's corporate bond yield spread changes, using each bond's 2004 par value held as the weight. A bond's yield spread change is its yield spread at the end of 2005Q4 minus that at the end of 2005Q2, where a yield spread is a bond's yield to maturity minus that on a maturity-matched Treasury.
Life	An indicator variable equal to 1 if more than 50% of portfolio assets are held by insurance companies in the group that are categorized by A.M. Best as providing life insurance, 0 otherwise.
Life_Pair	An indicator variable equal to 1 if Life=1 for both insurers in a pair, 0 otherwise.
Non-PSIFI	An indicator variable equal to 1 if an insurer (excluding separate accounts) does not meet the $50 billion in assets SIFI designation threshold in any year during the sample period, 0 otherwise.
Non-PSIFI_Pair	An indicator variable equal to 1 if Non-PSIFI=1 for both insurers in a pair, 0 otherwise.
PC	An indicator variable equal to 1 if more than 50% of portfolio assets are held by insurance companies in the group that are categorized by A.M. Best as providing property and casualty insurance, 0 otherwise.
PC_Pair	An indicator variable equal to 1 if PC=1 for both insurers in a pair, 0 otherwise.
PostCrisis	An indicator variable equal to 1 for the years 2010 to 2014, 0 otherwise.
Prod_Conc_AC or Prod_Conc_I	The product of Conc_AC or Conc_I for an insurer pair.
Prod_RBC	The natural logarithm of the product of RBC for an insurer pair.
Prod_Size	The natural logarithm of the product of portfolio assets for an insurer pair.
PSIFI	An indicator variable equal to 1 if an insurer could potentially be designated as a SIFI because it has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period, 0 otherwise.
PSIFI_Pair	An indicator variable equal to 1 if PSIFI=1 for both insurers in a pair, 0 otherwise.
RBC	A measure of capital adequacy calculated as the ratio of total adjusted capital to authorized control level risk-based capital (RBC). The RBC ratio at the insurer group level is constructed by (i) calculating the RBC ratio for each company in a group and (ii) computing the group RBC ratio as the weighted average of company RBC ratios using each company's total assets as weights.
RBC _Low_Pair	An indicator variable equal to 1 if the RBC of both insurers in a pair is at or below the bottom quartile of RBC ratios in a given year, 0 otherwise.
RetCov_Pair	The annual return covariance of daily holding-period returns for an insurer pair.
Similarity_AC or Similarity_I	The cosine similarity between a pair of insurers' asset class (AC) or issuer (I) portfolio weights.
Similarity_Avg_AC or Similarity_Avg_I	A simple average of an insurer's portfolio similarities with all other insurers, at the asset class (AC) or issuer (I) level.
Similarity_AC_Illiquid	Similarity_AC constructed using only illiquid asset classes: corporate bonds (all industries), municipal bonds (all types), RMBS, CMBS, and ABS.
Similarity_AC_Liquid	Similarity_AC constructed using only liquid asset classes: equity (all industries), mutual fund shares, U.S. government securities, GSE securities, and sovereign bonds.
Similarity_I_Downgraded	Similarity_I constructed using only issuers downgraded from investment grade to non-investment grade in the following year.
Similarity_I_NotDowngraded	Similarity_I constructed using only issuers not downgraded from investment grade to non-investment grade in the following year.
Size	The natural logarithm of an insurer's portfolio assets.
Total_Sales_AC or Total_Sales_I	The natural logarithm of an insurer's total net sales at the asset class (AC) or issuer (I) level.

Appendix C: Cluster Analysis

Cluster Algorithm

Cluster analysis could be performed using several algorithms that differ significantly in their notion of what constitutes a cluster and how to efficiently find clusters. The approach used in our paper is largely based on the concept that clusters are groups with small distances among the cluster members with particular statistical distributions. As described in more detail below, we apply internal validation measures, namely *Dunn Index* (Dunn, 1974), *Silhouette Width* (Rousseeuw, 1987) and *Connectivity* (Handl et al., 2005), on the most utilized unsupervised clustering algorithms (Self Organizing Maps, Self Organizing Tree Maps, K-means, and hierarchical).

The optimal number of clusters (N_{opt}) is finally obtained by computing the mode of the optimal number of clusters across the 13 years of our sample (N_t).

$$N_{opt} = Mo(N_t) \tag{8}$$

Coherently, the optimal algorithm (C_{opt}) is derived by counting the number of times an algorithm appears as locally optimal over the 13 years (C_t) and selecting the maximum value.

$$C_{opt} = Max(\sum_{i=1}^{13} C_t) \tag{9}$$

We run the unsupervised *K-means* algorithm (MacQueen, 1967) yearly with the following setting:[25]

i) for the first year (Y_t with $t = 1$) the number of clusters is 3;

ii) for the following year (Y_t with $t = [2 : 13]$) the centroids are obtained from the cluster of the previous year (Y_{t-1}).

The constraint for the cluster number in the first year comes from the outcome of the validation step. The constraint for the centroids' structure in the other years is set to introduce a *short-time memory effect* in the evolution of the clusters over time. The link of the cluster structures over time allows us to observe the transition of insurers among clusters year by year.

We then analyze the clusters by examining:

i) their size, both in term of the number of insurers and the dollar value of insurers' assets;

ii) their centroids' structure;

iii) the transition of insurers among clusters over time.

The average structure of the 3 clusters' centroids ($\overline{x^i}$) is computed as the average over time of the centroids' components (x^i_t).

$$\overline{x^i} = \frac{1}{13} \sum_{t=1}^{13} (x^i_t) \tag{10}$$

[25] The algorithm is based on a finite number of cycles aimed at defining the optimal cluster centroids according to the minimization of the distance of the n data points from their respective cluster centers, represented by the following objective function: $J = \sum_{j=1}^{k} \sum_{i=1}^{n} \|x_i^j - c_j\|^2$ where x_i^j is a data point and c_j is the cluster center.

Finally the yearly net flow ($NetFlow_i$) for cluster i is computed as:

$$Flow_{it} = \sum_{j \neq i} I_{jt}In - \sum_{j=i} I_{jt}Out \tag{11}$$

The cluster validation process applied to the yearly dataset provides the best fitting algorithm for the number of clusters. Each validation methodology is applied yearly using *K-means* algorithm. The optimal number of clusters appears to be 3.[26]

Cluster Validation

To validate the cluster approach we select a set of measures that reflect the degree of compactness, connectedness, and separation of the cluster partitions, tested respectively with *Connectivity*, *Dunn Index* and *Silhouette Width*, respectively.

Connectivity (Handl et al., 2005): Connectivity estimates to what extent the nearest observations (in our case insurers) are placed in the same cluster. We define N as the number of observations in the sample, M as the number of attributes of each observation (namely the coordinates of the observation in an M-dimensional space), and $nn_{i(j)}$ as the j^{th} nearest neighbor of observation i. Let $x_{i,nn_{i(j)}}$ be

$$x_{i,nn_{i(j)}} = \begin{cases} 0, & \text{if } i \text{ and } j \text{ are in the same cluster} \\ \frac{1}{j}, & otherwise. \end{cases} \tag{12}$$

For a specific cluster partition $\mathcal{C} = \{C_1, ...C_k\}$ of the N observations, *connectivity* is defined as:

$$Conn(\mathcal{C}) = \sum_{i=1}^{N} \sum_{j=1}^{L} x_{i,nn_{i(j)}} \tag{13}$$

where L is the number of neighbors used. *Connectivity* has values between 0 and ∞ and should be minimized.

Silhouette Width (Rousseeuw, 1987): *Silhouette Width* is the average of each observation's Silhouette Value. *Silhouette Value* is defined as:

$$S(i) = \frac{b_i - a_i}{max(b_i, a_i)}, \tag{14}$$

where a_i is the average distance between observation i and the other observations belonging to the same cluster, and b_i is the average distance between i and the observations in the "nearest neighboring" cluster defined as:

$$b_i = \min_{C_k \in \mathcal{C} \ C(i)} \sum_{j \in C_k} \frac{dist(i,j)}{n(C_k)}, \tag{15}$$

where $C(i)$ is the cluster containing observation i, $dist(i,j)$ is the distance between observations i and j, and $n(C)$ is the cardinality of cluster C. *Silhouette Width* lies in the $[-1, 1]$ range and should be maximized.

[26] Details on the validation are provided upon request.

Dunn Index (Dunn, 1974): *Dunn Index* is the ratio of the smallest distance between observations not in the same cluster and the largest intra-cluster distance:

$$D(\mathcal{C}) = \frac{\min_{C_k, C_l \in \mathcal{C}, C(k) \neq C_l} (\min_{i \in C_k, j \in C_j} dist(i, j))}{\max_{C_m \in \mathcal{C}} diam(C_m)}, \tag{16}$$

where $diam(C_m)$ is the maximum distance between observations in cluster C_m. *Dunn Index* is in the $[0, \infty]$ range and should be maximized.

Figure 1: Portfolio Composition Through Time

This figure presents the composition of the aggregate insurance industry portfolio by primary asset class from 2002 to 2014.

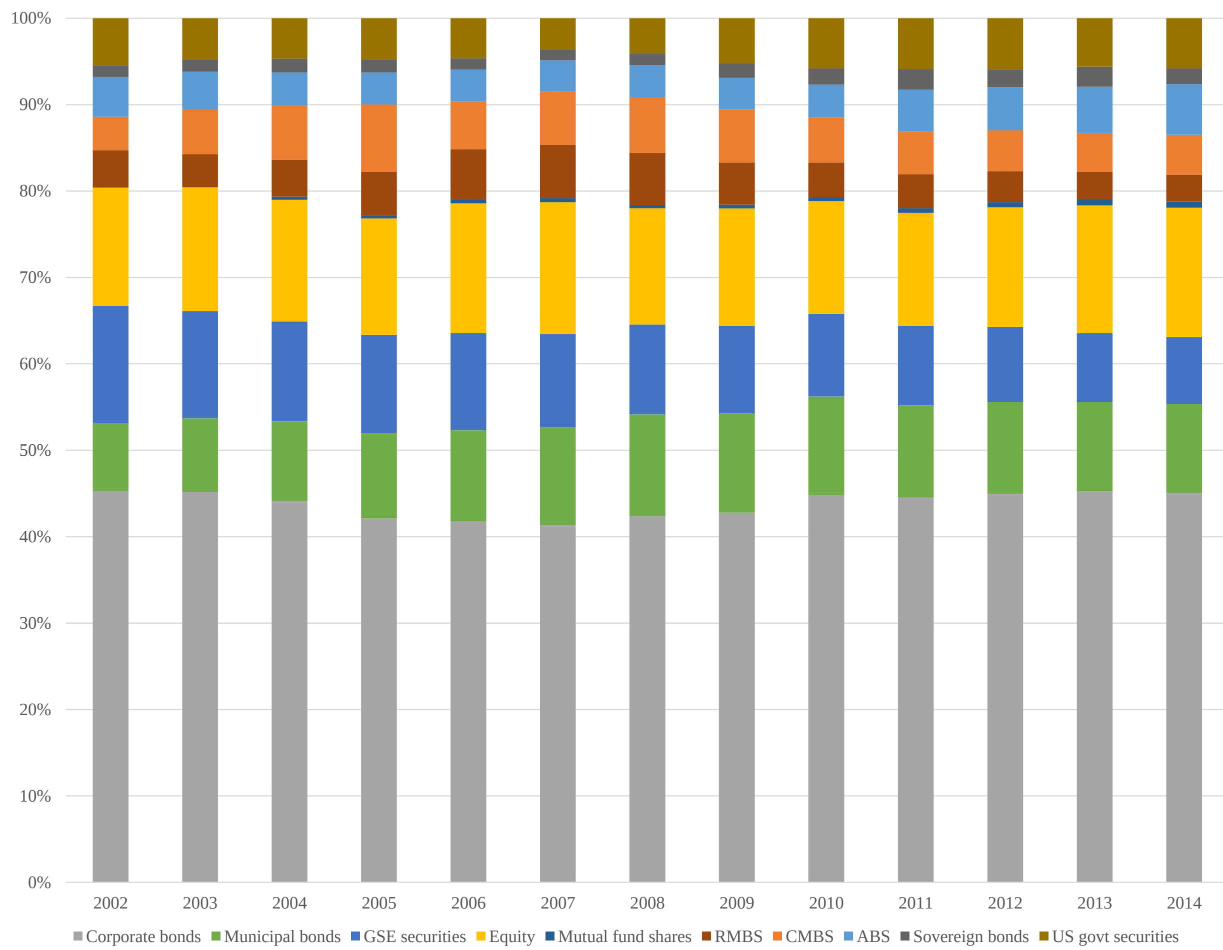


Figure 2: Portfolio Cluster Composition by Primary Asset Classes

This figure presents the average primary asset class dollar composition of the three clusters of insurer portfolios from 2002 to 2014.

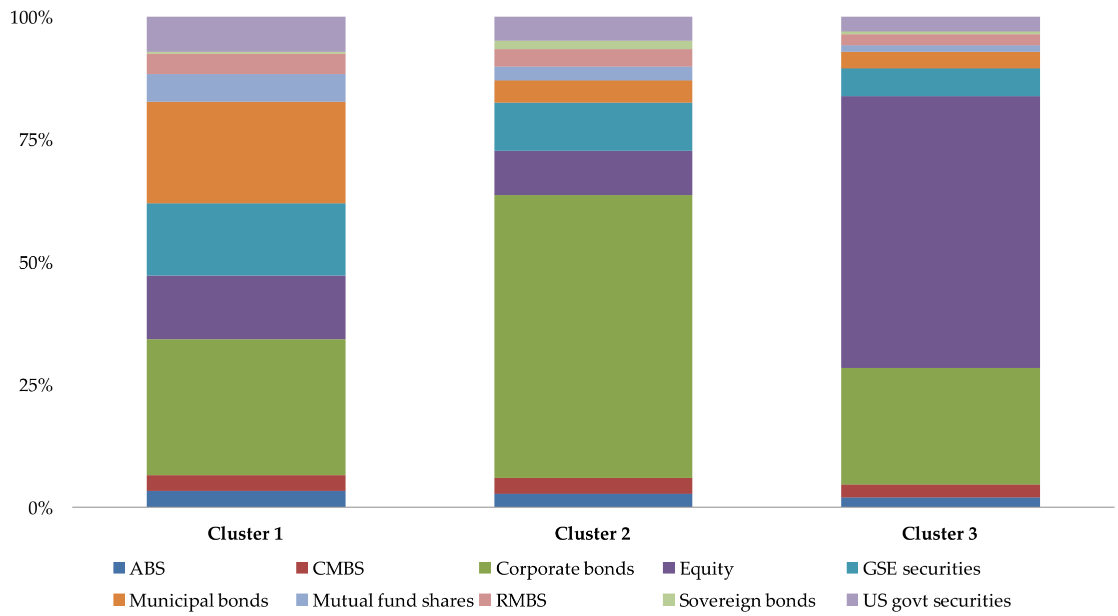
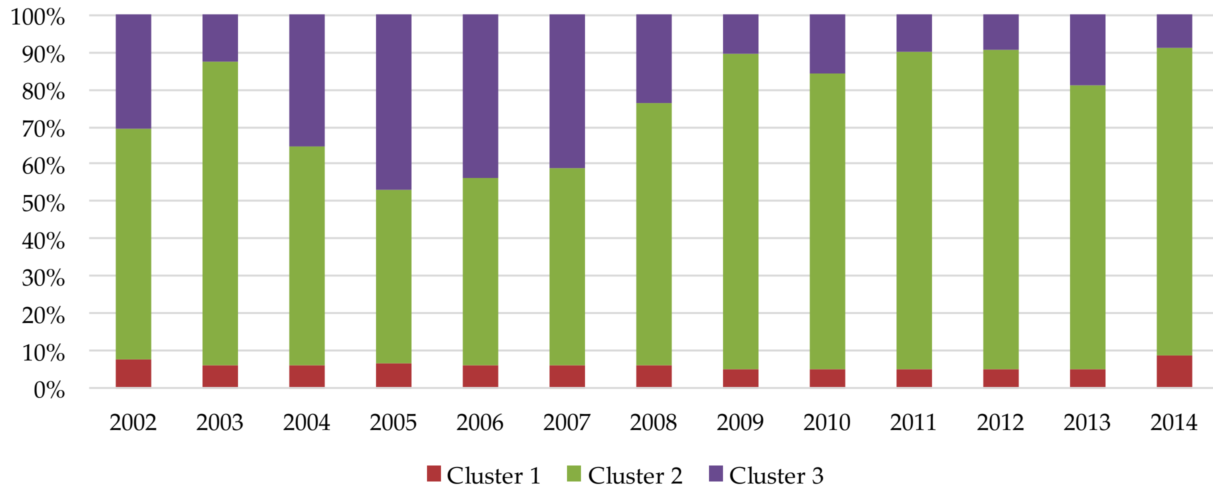
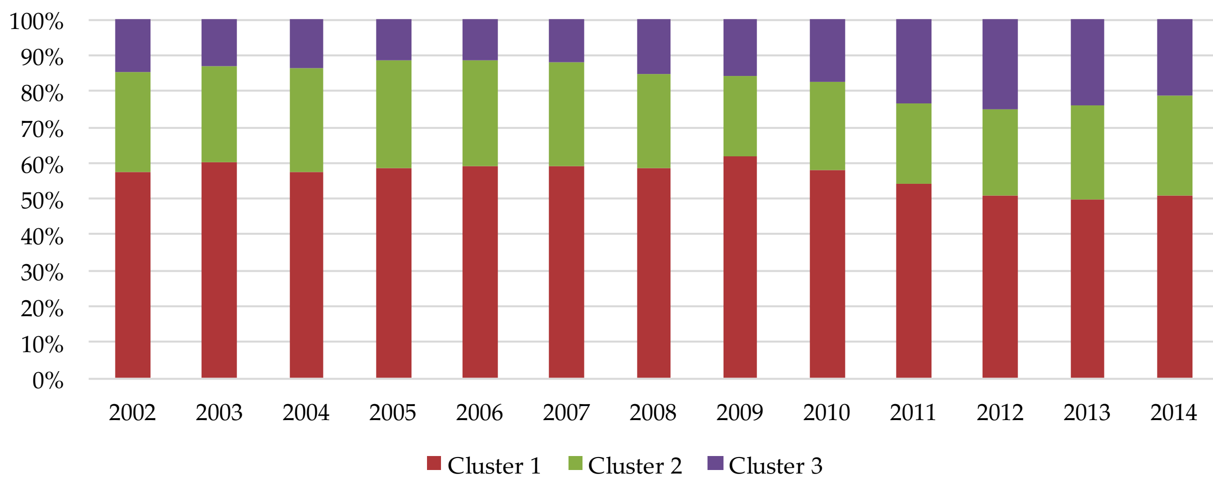


Figure 3: Distribution of PSIFIs and Non-PSIFIs in Portfolio Clusters

The figures present the distribution of PSIFI and non-PSIFI insurers among the three clusters from 2002 to 2014. PSIFI is an insurer that could potentially be designated a SIFI because it has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. Non-PSIFI is an insurer that does not meet the PSIFI definition.



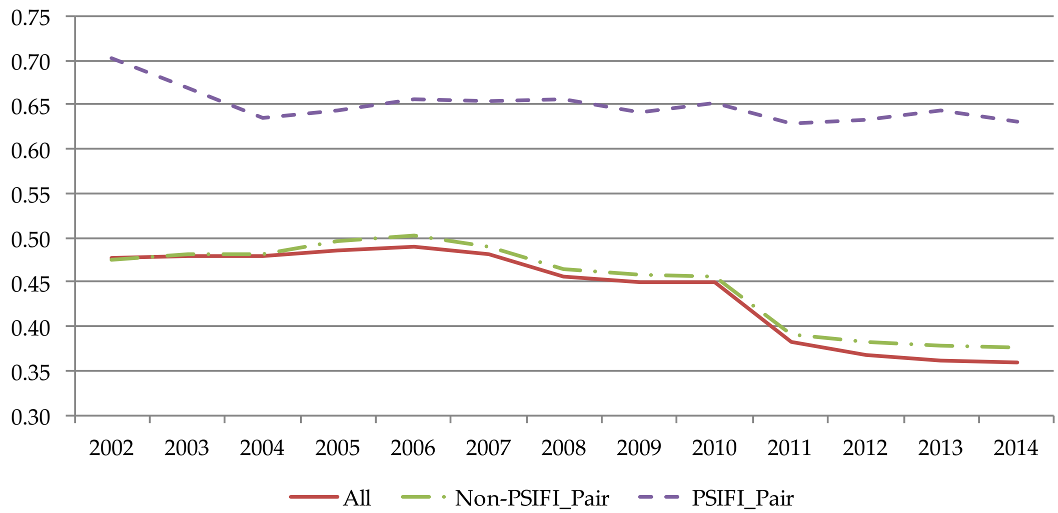
(a) PSIFI



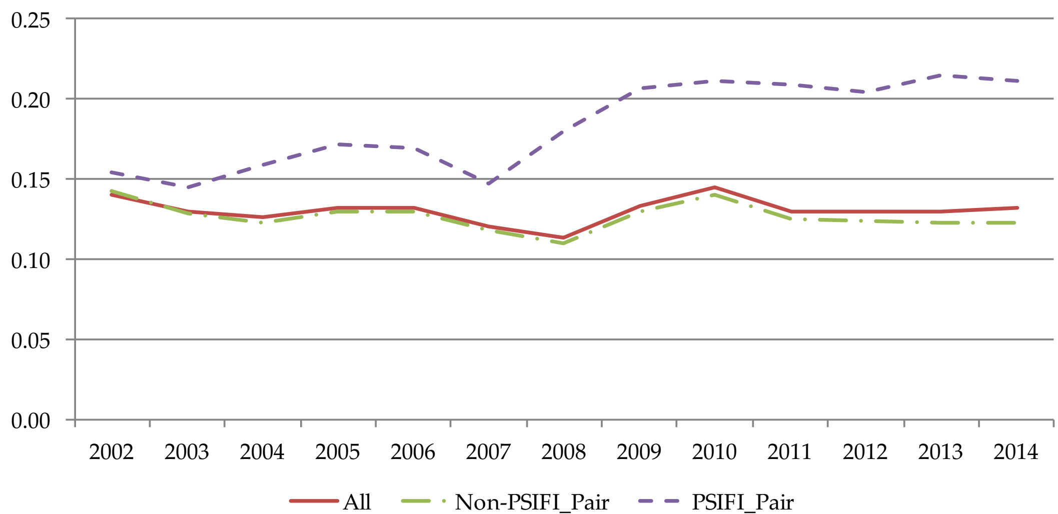
(b) Non-PSIFI

Figure 4: Portfolio Similarity Through Time

The figure presents average portfolio similarity at the (a) asset class level (*Similarity_AC*) and (b) issuer level (*Similarity_I*) from 2002 to 2014. PSIFI is an insurer that could potentially be designated a SIFI because it has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. Non-PSIFI is an insurer that does not meet the PSIFI definition. PSIFI (non-PSIFI) pairs are those where both insurers in the pair are classified as PSIFI (non-PSIFI).



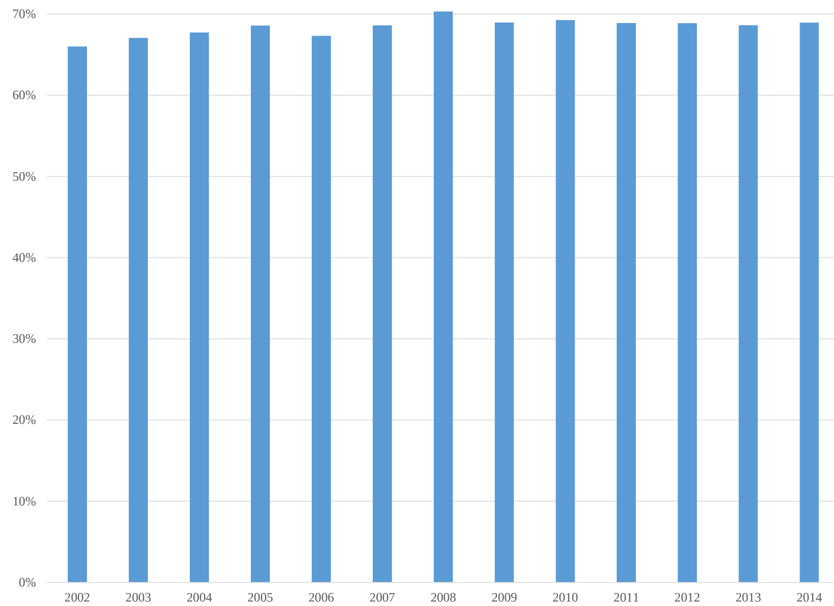
(a) Portfolio Similarity at the Asset Class Level



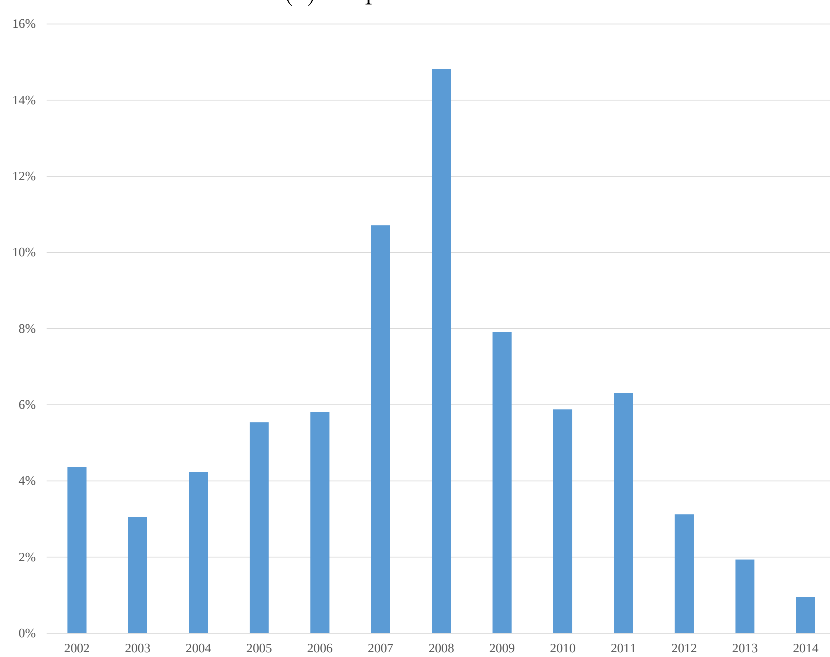
(b) Portfolio Similarity at the Issuer Level

Figure 5: Proportion of Illiquid and Downgraded Holdings

The figures present the proportion of holdings that are composed of (a) illiquid asset classes or (b) downgraded issuers from 2002 to 2014. Illiquid asset classes include corporate bonds (all industries), municipal bonds (all types), RMBS, CMBS, and ABS. Downgraded issuers are those that are downgraded from investment grade to non-investment grade in the following year.



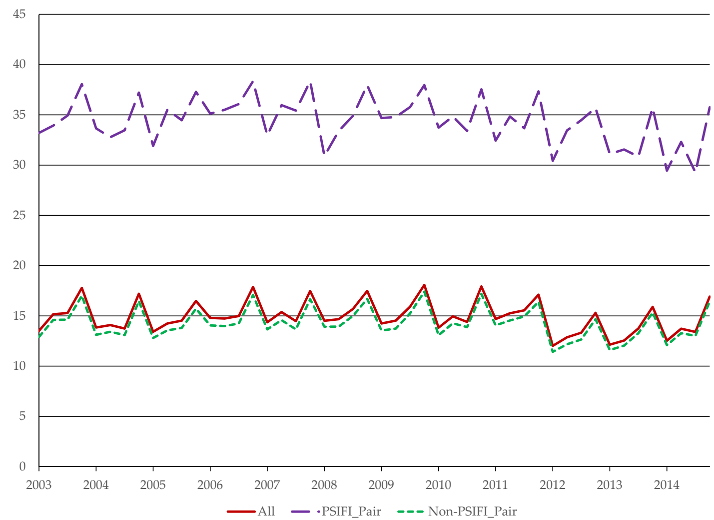
(a) Illiquid Asset Classes



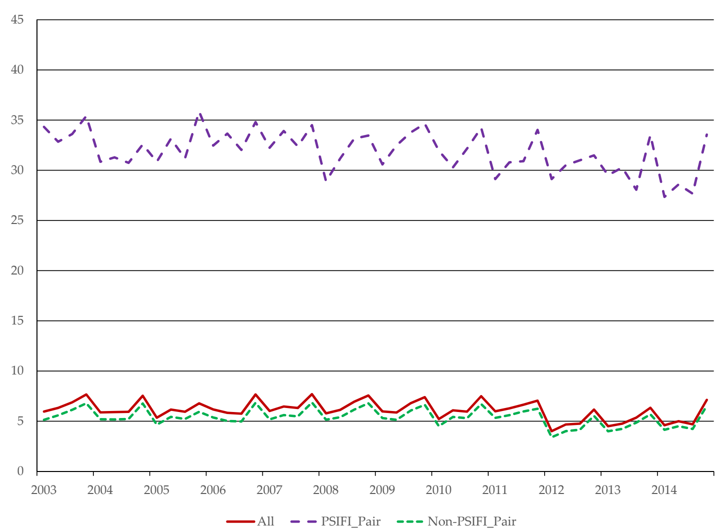
(b) Downgraded Issuers

Figure 6: Common Sales Through Time

The figures present the average of the natural logarithm of one plus quarterly common sales at the (a) asset class level (*Common Sales_AC*) or (b) issuer level (*Common Sales_I*) from 2002 to 2014. PSIFI is an insurer that could potentially be designated a SIFI because it has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. Non-PSIFI is an insurer that does not meet the PSIFI definition. PSIFI (non-PSIFI) pairs are those where both insurers in the pair are classified as PSIFI (non-PSIFI).



(a) Common Sales at the Asset Class Level



(b) Common Sales at the Issuer Level

Table 1: Portfolio Composition and Other Insurer Characteristics

The table presents statistics on portfolio composition and other characteristics for the sample of insurers from 2002 to 2014. Life insurers operate predominantly in life lines of business. P&C insurers operate predominantly in property and casualty lines of business. *PSIFI* is an insurer that has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. *Non-PSIFI* is an insurer that does not meet the PSIFI definition. *TA* is total assets. Investment portfolio is the dollar value of portfolio holdings disclosed on Schedule D. Corporate bonds, GSE debt securities, municipal bonds, U.S. government securities, RMBS, CMBS, ABS, sovereign bonds, equity, and mutual fund shares are the dollar-value percentages of an insurer's portfolio invested in these primary asset classes. Number of issues is the number of unique 9-digit CUSIPs in an insurer's portfolio. Number of issuers is the number of unique issuers, identified using 6-digit CUSIPs in an insurer's portfolio. *Conc_AC* or *Conc_I* is a Herfindahl index constructed for each insurer as the sum of the squared weights of asset classes or issuers in its portfolio. Asset class/issuer weights are calculated as the dollar amount invested in each asset class/issuer relative to the total value of an insurer's portfolio. Mean, medians and standard deviations are based on the cross-sectional variation of insurers' time series average.

	All (N=2,812)			Life (N=635)			P&C (N=1,746)			PSIFI (N=38)			Non-PSIFI (N=2,381)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Insurer Characteristics															
TA incl separate accounts ($B)	3.25	0.06	23.30	11.19	0.08	47.25	0.85	0.05	4.20	145.12	87.70	117.39	1.01	0.05	4.31
TA excl separate accounts ($B)	2.41	0.06	15.42	7.54	0.08	30.67	0.85	0.05	4.20	99.80	67.89	71.84	0.87	0.05	3.26
Investment portfolio ($B)	1.65	0.04	10.46	5.04	0.07	19.75	0.89	0.03	6.18	36.63	30.08	24.60	0.39	0.03	1.40
Primary Asset Class Composition (%)															
Corporate bonds	27.1	24.1	22.3	36.4	36.7	24.0	23.7	21.4	19.4	52.7	56.9	18.4	26.9	24.0	22.0
GSE debt securities	19.3	15.4	19.3	20.7	15.4	20.1	19.2	15.9	18.6	12.1	8.2	12.7	19.6	15.9	19.2
Municipal bonds	14.4	4.5	20.5	7.6	2.3	13.7	18.3	9.8	21.9	5.5	2.9	9.2	15.9	6.0	21.2
U.S. government securities	15.4	5.8	23.8	14.2	3.9	24.9	14.8	6.1	21.8	3.2	0.9	4.4	14.8	5.4	22.8
RMBS	1.4	0.0	4.1	2.7	0.2	5.6	1.2	0.0	3.8	6.6	5.3	7.8	1.3	0.0	4.3
CMBS	1.8	0.0	3.3	2.6	0.3	3.9	1.6	0.0	3.1	5.6	5.3	2.9	1.7	0.0	3.3
ABS	1.7	0.0	3.5	2.3	0.7	4.0	1.6	0.0	3.3	5.6	4.6	5.3	1.6	0.0	3.5
Sovereign bonds	0.3	0.0	1.5	0.4	0.0	2.2	0.2	0.0	1.4	1.3	0.3	4.9	0.2	0.0	2.0
Equity	13.6	7.2	18.4	11.6	5.1	17.9	14.2	9.0	17.2	7.2	4.8	6.4	13.3	7.2	17.8
Mutual fund shares	5.1	0.1	13.7	1.5	0.0	6.7	5.2	0.1	13.8	0.2	0.0	0.3	4.7	0.0	13.1
Issue/Issuer Composition															
Number of issues	380	116	1,074	748	174	1,790	291	111	812	3,704	3,204	2,661	223	109	363
Number of issuers	250	100	493	440	137	809	203	97	363	1,888	1,705	922	172	95	243
Concentration															
Conc_AC	0.31	0.20	0.26	0.28	0.16	0.26	0.30	0.20	0.24	0.12	0.10	0.08	0.30	0.20	0.25
Conc_I	0.16	0.04	0.25	0.14	0.03	0.25	0.14	0.04	0.22	0.01	0.00	0.02	0.14	0.04	0.23

Table 2: Summary Statistics for Portfolio Similarity and Common Sales

The table presents summary statistics for portfolio similarity and common sales for insurer pairs from 2002 to 2014. *PSIFI* is an insurer that has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. Non-PSIFI is an insurer that does not meet the PSIFI definition. PSIFI (non-PSIFI) pairs are those where both insurers in the pair are classified as PSIFI (non-PSIFI). *Similarity_AC* or *Similarity_I* is the cosine similarity between a pair's asset class or issuer portfolio weights. *Similarity_AC_Liquid* is asset-class portfolio similarity constructed using only liquid asset classes: equity, mutual fund shares, U.S. government securities, GSE securities, and sovereign bonds. *Similarity_AC_Illiquid* is asset-class portfolio similarity constructed using only illiquid asset classes: corporate bonds, municipal bonds, RMBS, CMBS, and ABS. *Similarity_I_Downgraded* is issuer portfolio similarity constructed using only issuers downgraded from investment to non-investment grade in the following year. *Similarity_I_NotDowngraded* is issuer portfolio similarity constructed using only issuers not downgraded from investment to non-investment grade in the following year. *Common Sales_AC* or *Common Sales_I* is the dot product of a pair's asset class or issuer level net sales. P25, P50 and P75 indicate the 25th, 50th, and 75th percentile of the distribution.

	All Pairs					PSIFI Pairs					Non-PSIFI Pairs				
	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
Similarity_AC	0.45	0.27	0.22	0.45	0.68	0.65	0.22	0.52	0.70	0.82	0.45	0.28	0.21	0.45	0.68
Similarity_I	0.12	0.18	0.01	0.05	0.15	0.18	0.15	0.07	0.14	0.26	0.12	0.18	0.01	0.05	0.16
Similarity_AC_Liquid	0.54	0.34	0.23	0.59	0.86	0.67	0.25	0.53	0.73	0.88	0.54	0.34	0.23	0.59	0.86
Similarity_AC_Illiquid	0.42	0.31	0.13	0.43	0.69	0.74	0.21	0.64	0.81	0.90	0.42	0.31	0.13	0.43	0.69
Similarity_I_Downgraded	0.07	0.15	0.00	0.00	0.06	0.41	0.21	0.25	0.44	0.58	0.07	0.15	0.00	0.00	0.04
Similarity_I_NotDowngraded	0.13	0.18	0.01	0.05	0.16	0.17	0.15	0.06	0.13	0.25	0.13	0.18	0.01	0.05	0.16
Ln(1+Common Sales_AC)	14.92	13.84	0.00	21.96	27.67	34.42	7.93	33.85	36.04	37.98	14.27	13.63	0.00	20.92	27.19
Ln(1+Common Sales_I)	6.07	11.32	0.00	0.00	0.00	31.89	9.66	32.34	34.42	36.08	5.38	10.67	0.00	0.00	0.00

Table 3: Determinants of Portfolio Similarity

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is *Similarity_AC* or *Similarity_I*, defined as the cosine similarity between a pair's asset class or issuer portfolio weights. *Life_Pair* is an indicator variable equal to 1 if both insurers in a pair are life insurers, 0 otherwise. *PC_Pair* is an indicator variable equal to 1 if both insurers in a pair are P&C insurers, 0 otherwise. *PSIFI_Pair* is an indicator variable equal to 1 if both insurers in a pair have $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period, 0 otherwise. *Non-PSIFI_Pair* is an indicator variable equal to 1 if both insurers do not meet the PSIFI definition, 0 otherwise. *Prod_Size* is the natural logarithm of the product of a pair's portfolio assets. *Prod_Conc_AC* or *Prod_Conc_I* is the product of a pair's portfolio Herfindahl indices at the asset class or issuer level. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	Portfolio Similarity - Asset Class			Portfolio Similarity - Issuer		
	All Pairs (1)	PSIFI Pairs (2)	Non-PSIFI Pairs (3)	All Pairs (4)	PSIFI Pairs (5)	Non-PSIFI Pairs (6)
Life_Pair	0.058***	0.183***	0.051***	-0.005***	0.027***	-0.006***
	(8.06)	(21.48)	(6.50)	(-3.51)	(3.69)	(-4.33)
PC_Pair	0.035***	0.087***	0.033***	0.028***	0.035**	0.028***
	(8.20)	(7.16)	(7.42)	(22.10)	(2.30)	(20.34)
PSIFI_Pair	0.086***			0.051***		
	(13.63)			(15.03)		
NonPSIFI_Pair	0.127***			0.017***		
	(25.68)			(4.65)		
Prod_Size	0.016***	-0.020***	0.015***	0.003***	0.005	0.003***
	(24.50)	(-3.55)	(23.29)	(6.01)	(1.03)	(5.72)
Prod_Conc_AC	-0.333***	-22.250***	-0.330***			
	(-16.71)	(-8.73)	(-16.64)			
Prod_Conc_I				0.579***	-111.707***	0.577***
				(14.64)	(-7.12)	(14.69)
Year FE	YES	YES	YES	YES	YES	YES
N	10,605,950	6,608	10,078,140	10,605,950	6,608	10,078,140
Adj R^2	0.106	0.436	0.104	0.029	0.064	0.029

Table 4: Portfolio Similarity as a Determinant of Common Sales

The table presents probit/tobit estimation results for the sample of insurer pairs from 2002 to 2014. In columns (1) and (5), the dependent variable is an indicator variable equal to 1 if the natural logarithm of one plus *Common Sales_AC* or *Common Sales_I*, defined as the dot product of a pair's asset class or issuer net sales, is positive, 0 otherwise. In columns (2)–(4) and (6)–(8), the dependent variable is the natural logarithm of one plus *Common Sales_AC* or *Common Sales_I*. *Similarity_AC* or *Similarity_I* is the cosine similarity between a pair's asset class or issuer portfolio weights. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	Common Sales - Asset Class				Common Sales - Issuer			
	All Pairs Probit (1)	All Pairs Tobit (2)	PSIFI Pairs Tobit (3)	Non-PSIFI Pairs Tobit (4)	All Pairs Probit (5)	All Pairs Tobit (6)	PSIFI Pairs Tobit (7)	Non-PSIFI Pairs Tobit (8)
Similarity_AC	0.244***	4.714***	4.640***	4.969***				
	(28.61)	(24.51)	(7.38)	(24.52)				
Similarity_I					1.101***	33.981***	17.628***	34.629***
					(44.31)	(40.48)	(19.87)	(39.48)
Life_Pair	-0.124***	-2.265***	-0.515**	-2.332***	-0.122***	-3.565***	0.586***	-4.665***
	(-14.64)	(-14.03)	(-2.15)	(-12.82)	(-11.78)	(-12.13)	(3.03)	(-12.83)
PC_Pair	0.137***	2.587***	0.419	2.717***	0.125***	3.635***	0.008	3.987***
	(25.97)	(22.53)	(1.10)	(23.34)	(19.65)	(19.90)	(0.02)	(20.85)
PSIFI_Pair	0.551***	1.903***			0.618***	2.133***		
	(15.69)	(7.74)			(29.88)	(4.85)		
NonPSIFI_Pair	-0.128***	-1.674***			-0.198***	-4.500***		
	(-9.27)	(-7.80)			(-22.16)	(-18.51)		
Prod_Size	0.082***	1.918***	1.200***	1.945***	0.132***	4.222***	1.387***	4.357***
	(41.08)	(59.52)	(12.00)	(58.45)	(55.14)	(69.16)	(9.80)	(65.44)
Prod_Conc_AC	-3.303***	-65.265***	-13.910	-64.997***				
	(-28.88)	(-26.63)	(-0.46)	(-26.06)				
Prod_Conc_I					-1.815***	-43.989***	-7,669.241***	-42.068***
					(-4.50)	(-3.77)	(-7.22)	(-3.57)
Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
N	18,247,630	18,247,630	23,440	16,945,757	18,940,884	18,940,884	23,564	17,591,218
Pseudo R^2	0.067	0.024	0.018	0.020	0.115	0.046	0.025	0.037

Table 5: Common Sales and Return Covariance

The table presents tobit estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is the natural logarithm of one plus *Common Sales_AC* or *Common Sales_I*, defined as the dot product of a pairs asset class or issuer net sales. *Ret_Cov_Pair* is the annual return covariance of daily holding-period returns for the pair. *Similarity_AC* or *Similarity_I* is the cosine similarity between a pair's asset class or issuer portfolio weights. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	Common Sales - Asset Class				Common Sales - Issuer			
	All Pairs (1)	All Pairs (2)	PSIFI Pairs (3)	Non-PSIFI Pairs (4)	All Pairs (5)	All Pairs (6)	PSIFI Pairs (7)	Non-PSIFI Pairs (8)
Ret_Cov_Pair	118.667	-3.106	-604.330**	991.124	-402.182	-128.375	-480.803**	-1,570.928**
	(0.46)	(-0.01)	(-2.10)	(1.33)	(-1.31)	(-0.45)	(-1.97)	(-2.10)
Similarity_AC		4.615***	5.703***	6.553***				
		(6.61)	(4.56)	(7.42)				
Similarity_I						43.359***	22.425***	55.104***
						(31.05)	(12.38)	(29.29)
Life_Pair	-0.060	-0.718**	2.487**	-1.278***	1.694***	0.069	2.271**	-0.550
	(-0.18)	(-2.06)	(2.08)	(-2.63)	(3.97)	(0.17)	(1.98)	(-0.88)
PC_Pair	2.080***	1.822***		2.321***	-1.914**	-0.256		-0.368
	(3.08)	(2.70)		(3.00)	(-2.25)	(-0.33)		(-0.38)
PSIFI_Pair	1.113***	0.799**			-0.091	-0.942**		
	(2.93)	(2.14)			(-0.19)	(-2.01)		
NonPSIFI_Pair	-1.614***	-1.706***			-1.423***	-2.015***		
	(-3.51)	(-3.64)			(-3.35)	(-4.95)		
Prod_Size	2.037***	2.062***	2.133***	2.181***	4.090***	4.127***	3.200***	4.826***
	(20.89)	(21.10)	(10.19)	(18.20)	(34.88)	(34.34)	(14.11)	(27.80)
Prod_Conc_AC	-76.150***	-66.497***	-43.032**	-63.014**				
	(-5.17)	(-4.70)	(-2.36)	(-2.09)				
Prod_Conc_I					-2,108.262***	-1,938.606***	-8,527.551***	-994.302**
					(-3.57)	(-3.73)	(-6.59)	(-2.01)
Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
N	65,473	65,473	7,058	28,889	69,216	69,216	7,320	30,780
Pseudo R^2	0.028	0.028	0.026	0.019	0.048	0.057	0.048	0.041

Table 6: Common Sales and Asset Liquidity/Downgrades

The table presents tobit estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is the natural logarithm of one plus *Common Sales_AC* or *Common Sales_I*, defined as the dot product of a pair's asset class or issuer net sales. *Similarity_AC_Liquid* is a pair's asset-class portfolio similarity constructed using only liquid asset classes: equity, mutual fund shares, U.S. government securities, GSE securities, and sovereign bonds. *Similarity_AC_Illiquid* is a pair's asset-class portfolio similarity constructed using only illiquid asset classes: corporate bonds, municipal bonds, RMBS, CMBS, and ABS. *Similarity_I_Downgraded* is a pair's portfolio similarity constructed using only issuers downgraded from investment to non-investment grade in the following year. *Similarity_I_NotDowngraded* is a pair's portfolio similarity constructed using only issuers not downgraded from investment to non-investment grade in the following year. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	Common Sales - Asset Class			Common Sales - Issuer		
	All Pairs (1)	PSIFI Pairs (2)	Non-PSIFI Pairs (3)	All Pairs (4)	PSIFI Pairs (5)	Non-PSIFI Pairs (6)
Similarity_AC_Illiquid	3.216***	1.799***	3.402***			
	(16.38)	(3.46)	(16.63)			
Similarity_AC_Liquid	2.321***	4.275***	2.405***			
	(12.72)	(6.92)	(12.38)			
Similarity_I_Downgraded				24.539***	8.907***	25.615***
				(31.72)	(10.25)	(30.52)
Similarity_I_NotDowngraded				30.600***	12.995***	31.388***
				(36.28)	(15.42)	(35.38)
Life_Pair	-2.335***	-0.230	-2.408***	-3.920***	0.447**	-4.892***
	(-14.69)	(-1.07)	(-13.47)	(-13.66)	(2.26)	(-13.77)
PC_Pair	2.617***	0.459	2.744***	3.587***	0.428	3.956***
	(21.78)	(1.18)	(22.40)	(18.47)	(0.80)	(19.42)
PSIFI_Pair	1.911***			-2.346***		
	(7.99)			(-5.32)		
NonPSIFI_Pair	-1.622***			-4.536***		
	(-7.61)			(-18.15)		
Prod_Size	1.907***	1.264***	1.934***	3.942***	1.019***	4.091***
	(59.88)	(12.43)	(58.90)	(71.68)	(6.84)	(67.43)
Prod_Conc_AC	-63.853***	-17.698	-63.463***			
	(-26.34)	(-0.58)	(-25.79)			
Prod_Conc_I				-22.648**	-6,085.102***	-20.412*
				(-2.16)	(-6.46)	(-1.92)
Year-Quarter FE						
	18,068,519	23,440	16,766,652	18,940,884	23,564	17,591,218
N	YES	YES	YES	YES	YES	YES
Adj R^2	0.024	0.019	0.021	0.049	0.029	0.040

Table 7: Common Sales and Regulatory Capital Constraints

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is the natural logarithm of one plus *Common Sales_AC* or *Common Sales_I*, defined as the dot product of a pair's asset class or issuer net sales. The sample is restricted to insurer pairs that sell at least on asset class or issuer in common. *Similarity_AC* or *Similarity_I* is the cosine similarity between a pair's asset class or issuer portfolio weights. *Prod_RBC* is the natural logarithm of the product of a pair's RBC ratios (total adjusted capital to authorized control level risk-based capital). *RBC_Low_Pair* is an indicator variable equal to 1 if the RBC ratio of both insurers in a pair is at or below the bottom quartile of RBC ratios in a given year, 0 otherwise. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	Common Sales - Asset Class			Common Sales - Issuer		
	All Pairs (1)	PSIFI Pairs (2)	Non-PSIFI Pairs (3)	All Pairs (4)	PSIFI Pairs (5)	Non-PSIFI Pairs (6)
Similarity_AC	0.524***	1.733***	0.467***			
	(9.98)	(8.24)	(8.87)			
Similarity_I				4.404***	5.749***	4.287***
				(30.79)	(15.04)	(30.44)
Prod_RBC	-0.025**	-0.012	-0.021*	-0.036***	0.005	-0.033**
	(-2.31)	(-0.08)	(-1.99)	(-3.05)	(0.05)	(-2.63)
RBC_Low_Pair	0.304***	1.029	0.287***	0.414***	-0.675	0.401***
	(6.33)	(1.05)	(5.86)	(8.39)	(-0.51)	(8.01)
Similarity_AC×RBC_Low_Pair	0.208***	-0.306	0.248***			
	(3.00)	(-0.15)	(3.47)			
Similarity_I×RBC_Low_Pair				-0.239	9.235	-0.184
				(-1.46)	(1.45)	(-1.10)
Life_Pair	-0.059	0.160	-0.071*	0.206***	0.593***	0.180***
	(-1.63)	(1.15)	(-1.78)	(6.53)	(6.47)	(5.21)
PC_Pair	0.213***	-0.168	0.230***	-0.160***	-0.887***	-0.117***
	(6.77)	(-1.19)	(7.24)	(-5.74)	(-6.55)	(-3.95)
PSIFI_Pair	0.696***			0.935***		
	(12.45)			(20.22)		
NonPSIFI_Pair	-0.155***			0.170***		
	(-3.36)			(4.22)		
Prod_Size	0.743***	0.814***	0.742***	0.728***	0.737***	0.722***
	(95.47)	(11.86)	(98.53)	(81.58)	(14.13)	(83.19)
Prod_Conc_AC	1.834***	19.324	1.877***			
	(3.75)	(1.44)	(3.83)			
Prod_Conc_I				20.858***	-90.567	20.455***
				(13.25)	(-0.30)	(13.37)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
N	9,434,682	22,456	8,485,842	4,298,490	21,750	3,608,715
Adj R^2	0.450	0.202	0.397	0.427	0.226	0.367

Table 8: Bank and AIG Exposures

Panel (a) presents Tobit estimation results for the sample of insurer pairs from 2002 to 2014 for all pairs and those exposed to banks or AIG. The dependent variable is the natural logarithm of one plus *Common Sales_I*, defined as the dot product of a pair's issuer net sales. The sample is restricted to insurer pairs that sell at least one issuer in common. Robust t-statistics are in parentheses. *Similarity_I* is the cosine similarity between a pair's issuer portfolio weights and is computed in 2007. *Lehman* is an indicator variable equal to 1 in the third and fourth quarters of 2008 corresponding to the Lehman's bankruptcy filing and subsequent bankruptcy. For bank exposure, *Exposed* is an indicator variable equal to 1 if both insurers' portfolio holdings of financial firm corporate debt securities dollar value held relative to total corporate debt securities dollar value held is at or above the 75th percentile of the sample in that year. For AIG exposure, *Exposed* is an indicator variable equal to 1 if both insurers' portfolio similarity with AIG at the issuer level is above the median level in that year. Mixed pairs are those comprised of exposed (to banks or AIG) and non-exposed insurers. Panel (b) presents cross-sectional OLS estimation for the sample of insurer pairs for which the dependent variable can be calculated. The dependent variable is a pair's joint portfolio yield spread change from 2008Q2 (prior to Lehman's bankruptcy filing) to 2008Q4 (after the Lehman's bankruptcy filing), defined as the weighted average of the insurers in the pair's portfolio yield spread change, using the par value of the bonds held by each insurer at the end of 2007 as the weight. The yield spread change of a bond is its yield spread at the end of 2008Q4 minus the yield spread at the end of 2008Q2, where a yield spread is the bond's yield to maturity minus that on a maturity-matched Treasury. *Avg. Ln(Trades)* is the weighted average of the number of trades in the two quarters prior to the Lehman's bankruptcy filing; *Avg. Ln(Amt)* is the weighted average of the natural logarithm of the bonds' issuance amount; and *Avg. Ln(Mat)* is the weighted average natural logarithm of the bond's years to maturity. Standard errors are in parentheses. The remaining independent variables are defined in Appendix B and are measured as of the year-end prior to the sales quarter. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

(a) Common Sales

	Common Sales - Issuer			
	All Pairs Bank Exposed (1)	Only Exposed Pairs Bank Exposed (2)	All Pairs AIG Exposed (3)	Only Exposed Pairs AIG Exposed (4)
Similarity_I×Lehman×Exposed	4.380***		11.800***	
	(4.06)		(5.15)	
Similarity_I	34.473***	29.274***	31.625***	28.869***
	(39.67)	(20.60)	(21.82)	(32.73)
Similarity_I×Lehman	0.331	4.077*	-4.024	5.405***
	(0.18)	(1.86)	(-1.21)	(2.94)
Similarity_I×Exposed	-9.358***		-4.275**	
	(-8.77)		(-2.35)	
Lehman×Exposed	-2.993***		-0.506	
	(-5.25)		(-0.71)	
Lehman	4.689***	7.475***	4.546***	2.091***
	(17.56)	(17.10)	(24.21)	(6.25)
Exposed	0.403		4.346***	
	(1.04)		(15.80)	
Life_Pair	-3.565***	-4.301***	-3.754***	-3.419***
	(-12.14)	(-4.29)	-13.10	(-10.78)
PC_Pair	3.657***	0.317	3.927***	2.896***
	(20.30)	(0.55)	(21.97)	(11.81)
PSIFI_Pair	2.166***		2.680***	-0.391
	(5.01)		(6.13)	(-0.99)
NonPSIFI_Pair	-4.517***		-4.412***	-3.450***
	(-18.65)		(-17.86)	(-11.06)
Prod_Size	4.211***	3.716***	4.118***	4.178***
	(70.65)	(31.37)	(76.29)	(96.94)
Prod_Conc_I	-43.155***	-89.158***	-27.770***	-7.014
	(-3.72)	(-3.28)	(-2.76)	(-0.60)
Observations	18,940,884	1,010,235	18,908,222	6,015,013
Year-Quarter FE	YES	YES	YES	YES
Pseudo R-squared	0.046	0.022	0.046	0.043

(b) Price Impact

	All Pairs Bank Exposed (1)	Only Exposed Pairs Bank Exposed (2)	All Pairs AIG Exposed (3)	Only Exposed Pairs AIG Exposed (4)
Similarity_I×Exposed	0.437***		0.160***	
	(0.029)		0.017	
Similarity_I	0.023***	0.275***	0.052***	0.094***
	(0.009)	(0.036)	(0.012)	(0.011)
Exposed	-0.086***		-0.095***	
	(0.006)		(0.003)	
Avg. Ln(Amount)	-0.110***	-0.615***	-0.100***	0.153***
	(0.003)	(0.013)	(0.003)	(0.006)
Avg. Ln(Maturity)	0.203***	0.217***	0.204***	0.079***
	(0.003)	(0.015)	(0.003)	(0.005)
Avg. Ln(Trades)	-0.381***	0.185***	-0.386***	-0.550***
	(0.003)	(0.013)	(0.003)	(0.005)
Life_Pair	-0.004	0.122**	-0.003	-0.019***
	(0.005)	(0.054)	(0.005)	(0.006)
PC_Pair	-0.061***	-0.049***	-0.068***	-0.117***
	(0.003)	(0.013)	(0.003)	(0.004)
Prod_Size	0.023***	-0.001	0.026***	0.019***
	(0.000)	(0.002)	(0.000)	(0.001)
Prod_Conc_I	1.813***	5.748***	1.388***	35.907***
	(0.212)	(0.938)	(0.217)	(1.336)
Prod_RBC	0.002*	-0.016***	0.002*	0.020***
	(0.001)	(0.004)	(0.001)	(0.001)
RBC_Low_Pair	-0.030***	-0.104***	-0.032***	-0.042***
	(0.005)	(0.022)	(0.005)	(0.007)
Constant	5.603***	9.647***	5.425***	3.295***
	(0.036)	(0.125)	(0.036)	(0.069)
Observations	398,490	23,819	397,590	156,978
R-squared	0.228	0.202	0.229	0.276

Table 9: Hurricane Exposure

Panel (a) presents tobit estimation for the sample of P&C insurer pairs from 2002 to 2014 where the dependent variable is the natural logarithm of one plus *Common Sales_I*, defined as the dot product of a pair's issuer net sales. *Similarity_I* is the cosine similarity between a pair's issuer portfolio weights. *Exposed* is an indicator variable equal to 1 if both insurers' premiums written in affected states (Mississippi and Louisiana) relative to all premiums written, are in the top quartile of the sample for the year, and 0 otherwise. *Hurricane* is an indicator variable equal to 1 in the third quarter of 2005, and 0 otherwise. The remaining independent variables are defined in Appendix B. Mixed pairs are those comprised of an exposed and non-exposed insurers. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Panel (b) presents cross-sectional OLS estimation for the sample of P&C insurer pairs for which the dependent variable can be calculated. The dependent variable is a pair's joint portfolio yield spread change from 2005Q2 (prior to Hurricanes Katrina and Rita) to 2005Q4 (after the hurricanes), defined as the weighted average of the insurers in the pair's portfolio yield spread change, using the par value of the bonds held by each insurer at the end of 2004 as the weight. An insurer's portfolio yield spread change is the weighted average yield spread change of the corporate bonds in its portfolio, using each bond's par value held at the end of 2004 as the weight. The yield spread change of a bond is its yield spread at the end of 2005Q4 minus the yield spread at the end of 2005Q2, where a yield spread is the bond's yield to maturity minus that on a maturity-matched Treasury. *Avg. Ln(Trades)* is the weighted average of the number of trades in the two quarters prior to the hurricanes; *Avg. Ln(Amt)* is the weighted average of the natural logarithm of the bonds' issuance amount; and *Avg. Ln(Mat)* is the weighted average natural logarithm of the bond's years to maturity. Standard errors are in parentheses. The remaining independent variables are defined in Appendix B and are measured as of the year-end prior to the sales quarter. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

(a) Common Sales

	All P&C Pairs (1)	Excluding Mixed Pairs (2)	Only Exposed Pairs (3)
Similarity_I	28.252***	27.327***	30.044***
	(36.04)	(36.28)	(22.15)
Similarity_I*Hurricane*Exposed	6.416***	8.853***	
	(5.80)	(6.18)	
Similarity_I*Hurricane	0.399	-1.795***	5.254***
	(0.57)	(-2.58)	(3.98)
Similarity_I*Exposed	2.006*	2.936**	
	(1.88)	(2.12)	
Hurricane*Exposed	1.822***	2.350***	
	(4.99)	(5.11)	
Hurricane	-1.011***	-1.295***	-0.366
	(-7.93)	(-9.23)	(-1.55)
Exposed	-2.021***	-3.150***	
	(-6.50)	(-7.56)	
Prod_Size	4.182***	4.259***	4.214***
	(63.00)	(61.50)	(52.85)
Prod_Conc_I	-40.656***	-30.213***	-103.693**
	(-3.35)	(-2.97)	(-2.39)
N	9,368,378	5,704,588	657,504
Pseudo R^2	0.036	0.036	0.042

(b) Price Impact

	All P&C Pairs (1)	Excluding Mixed Pairs (2)	Only Exposed Pairs (3)
Similarity_I	-0.070***	-0.152***	0.138***
	(0.007)	(0.009)	(0.023)
Exposed	-0.008	-0.026***	
	(0.005)	(0.005)	
Similarity_I*Exposed	0.098***	0.155***	
	(0.024)	(0.024)	
Avg. Ln(Trades)	0.181***	0.200***	0.084***
	(0.002)	(0.003)	(0.010)
Avg. Ln(Amount)	-0.165***	-0.159***	-0.139***
	(0.002)	(0.003)	(0.015)
Avg. Ln(Maturity)	0.032***	0.020***	0.080***
	(0.003)	(0.004)	(0.011)
Prod_Size	-0.015***	-0.010***	-0.028***
	(0.000)	(0.001)	(0.001)
Proc_Conc_I	-6.656***	-1.326***	-44.287***
	(0.255)	(0.305)	(1.521)
Prod_RBC	0.001	-0.000	0.009**
	(0.001)	(0.001)	(0.004)
RBC_Low_Pair	0.026***	0.018***	0.062***
	(0.004)	(0.005)	(0.013)
Constant	1.782***	1.445***	2.409***
	(0.025)	(0.030)	(0.162)
N	187,673	112,652	14,128
Adj. R^2	0.072	0.077	0.095

Table 10: Portfolio Similarity as a Determinant of Common Sales at the Insurer Level

The table presents tobit estimation results for the sample of insurers from 2002 to 2014. The dependent variable is the natural logarithm of one plus either *Common_Sales_Aggr_AC* or *Common_Sales_Aggr_I*, defined as the sum of an insurer's pairwise common sales with all other insurers, at the asset class or issuer level. *Similarity_Avg_AC* or *Similarity_Avg_I* is the average of an insurer's portfolio similarities with all other insurers at the asset class or issuer level. *Life* and *PC* are indicator variables equal to 1 if the insurer is a life or a P&C insurer respectively, and 0 otherwise. *PSIFI* is an indicator variable equal to 1 if an insurer has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period, and 0 otherwise. *Size* is the natural logarithm of an insurer's portfolio assets. *Conc_AC* or *Conc_I* is the concentration of an insurer's portfolio at the asset class or issuer level. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	Common Sales - Asset Class			Common Sales - Issuer		
	All Pairs (1)	PSIFI Pairs (2)	Non-PSIFI Pairs (3)	All Pairs (4)	PSIFI Pairs (5)	Non-PSIFI Pairs (6)
Similarity_Avg_AC	0.388***	3.329***	0.312**			
	(2.64)	(9.05)	(2.06)			
Similarity_Avg_I				13.039***	12.610***	13.092***
				(34.98)	(15.49)	(34.39)
Life	-0.123**	0.292*	-0.144**	-0.360***	0.112	-0.390***
	(-2.00)	(1.66)	(-2.27)	(-4.66)	(0.51)	(-4.84)
PC	0.151***	-0.361**	0.161***	-0.232***	-1.022***	-0.219***
	(3.03)	(-2.13)	(3.13)	(-2.92)	(-4.47)	(-2.70)
PSIFI	0.559***			-0.287***		
	(11.17)			(-3.14)		
Size	0.859***	0.682***	0.861***	1.317***	0.795***	1.322***
	(116.56)	(9.97)	(119.65)	(78.99)	(11.31)	(78.80)
Conc_AC	0.325***	3.366**	0.313***			
	(3.06)	(2.57)	(2.93)			
Conc_I				-1.653***	10.594**	-1.651***
				(-3.46)	(2.16)	(-3.44)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
N	41,821	1,524	40,297	43,478	1,528	41,950
Pseudo R^2	0.164	0.108	0.144	0.054	0.109	0.047