Portfolio Similarity and Asset Liquidation in the Insurance Industry*

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Abstract

Insurance companies have been designated as Systemically Important Financial Institutions (SIFI) based upon the presumption that large insurers have similar portfolios and this similarity has the potential to affect the asset liquidation channel of systemic risk transmission. Analyzing a comprehensive dataset of both public and private insurance companies from 2002 to 2014, we construct a portfolio similarity measure using cosine similarity. We show that greater portfolio similarity between two insurers is significantly related to the similarity in insurers' asset liquidation decisions and this relationship is only marginally related to whether or not insurer pairs are capital constrained. Potential SIFIs (insurers with $50 billion or more in consolidated assets), but not other insurers, with greater portfolio similarity of illiquid and downgraded securities have greater sales similarity during the financial crisis. This relationship remains strong even during the post-crisis period, providing support for the basis of their designation as systemically important. Our portfolio similarity measure provides information on the potential selling behavior of insurers over and above size and total sales. This work provides an implementable mechanism to identify and monitor the interconnectedness of insurer portfolios, thus helping regulators to identify asset liquidation channel vulnerabilities.

Keywords: Interconnectedness, Asset liquidation, Similarity, Systemic Risk, Financial Stability, Insurance Companies, SIFI

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> "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 de-leveraging could result in asset fire sales that cause significant damage to the broader economy." (emphasis added)
>
> Basis for the Financial Stability Oversight Council's Final Determination Regarding Prudential Financial, Inc.

1 Introduction

The recent global financial crisis of 2007-2009 exposed many vulnerabilities in the financial system, one of which was the implicit and explicit interconnectedness of financial institutions that led to the collapse of Lehman Brothers, Bear Stearns, Washington Mutual, Wachovia, and AIG, among others. In addition, the events of this period precipitated huge losses in several financial markets (e.g. stock, credit default swap, subprime mortgage, and money markets). Governments in the United States, United Kingdom, and several other Western European countries were forced to intervene in order to prevent further market declines.

Following the global financial crisis, the U.S. Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd-Frank Act). The Act created the Financial Stability Oversight Council (FSOC) and endowed the Council with the authority to designate bank and nonbank Systemically Important Financial Institutions (SIFIs). Companies that are designated as SIFIs are subject to enhanced prudential standards with the goal of limiting the effect of a SIFI's distress on financial stability. In designating nonbank financial institutions, such as insurance companies, asset management companies, savings and loan holding companies, broker-dealers, and other financial firms as SIFIs, a variety of factors have been considered by regulators with size and interconnectedness being the two most important ones.[1]

Although it is relatively straight-forward to measure the size of a financial institution (global assets, or for a foreign institution, U.S. total consolidated assets), there is no consensus on how

[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. 111203, 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 globally systemically important financial institutions (G-SIFIs) (see BIS (2014)).

to measure interconnectedness. Interconnectedness among financial institutions can arise in a variety of ways on both the asset and liability side of the balance sheet. Prior research that has focused on the contribution of insurers to systemic risk generally examines interconnectedness through operational risks, reinsurance, non-traditional investments, and financing. Harrington (2009) suggests that the systemic risk of property and casualty (P&C) insurers is low, while that of life insurers could be high because of higher leverage and potential policyholder withdrawals during a financial crisis. Cummins and Weiss (2014) conclude that the core activities of both life and P&C insurers are not a source of systemic risk, but the non-core activities of life insurers could make them systemically relevant. Koijen and Yogo (2016) show that life insurers use shadow reinsurance to move their liabilities from operating companies to less regulated and unrated off-balance-sheet entities within the same insurance group. These "shadow reinsurer" transactions do not decrease life insurers' risk as liabilities stay within the same insurance group. Reinsurance can also be a source of interconnectedness (Cummins and Weiss (2014) and Park and Xie (2014)), as can be insurers' increased exposure to derivatives (Geneva Association (2010) and Grace (2010)) and increased reliance on short-term funding (Geneva Association (2010)).

In this paper, we focus on the asset side of the balance sheet and examine whether the interconnectedness among the investment portfolios of insurers could contribute to systemic risk through the asset liquidation channel. The FSOC defines the asset liquidation channel as occurring when a "nonbank financial company holds assets that, if liquidated quickly, would cause a fall in asset prices and thereby significantly disrupt trading or funding in key markets or cause significant losses or funding problems for other firms with similar holdings."[2] We contribute to the literature in two ways. First, we outline a methodology that captures interconnectedness between pairs of insurers' portfolios. Second, we show how our measure of interconnectedness is related to the asset liquidation channel.

Asset liquidation can be triggered by asset valuation shocks (Brunnermeier and Pedersen (2005)), capital constraints (Ellul, Jotikasthira, and Lundblad (2011), Danielsson, Shin, and Zigrand (2004) and Brunnermeier and Pedersen (2009)), and sale of collateral (Shleifer and Vishny

[2]See *Basis for the Financial Stability Oversight Council's Final Determination Regarding Prudential Financial, Inc.* available on the FSOC website (FSOC (2013)). As of the writing of this paper, the FSOC has 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. and Prudential Financial, Inc.

(2011)). The price impact of such portfolio re-balancing is exacerbated when the securities sold are illiquid (Brunnermeier and Pedersen (2009) and Cont and Wagalath (2015)). According to Kartasheva (2014), insurers do not need to fail to propagate systemic risk; it may be sufficient for them to "fire sell" assets to produce a significant systemic impact.

The transmission of systemic risk through the asset liquidation channel is likely to occur if the portfolios of insurance companies are similar. When faced with a financial shock to either assets or liabilities, the assumption is that insurers will re-balance their portfolios in the same fashion thereby transmitting systemic risk throughout the economy. For example, Ben S. Bernanke states that "Examples of vulnerabilities include interconnectedness, and complexity, all of which have the potential to magnify shocks to the financial system. Absent vulnerabilities, triggers [such as losses on mortgage holdings] would generally not lead to full-blown financial crises."[3] However, little research has been conducted to examine the similarity of insurers' portfolios and whether it affects their selling behavior. While the Federal Reserve Board serves as a lender of last resort to bank holding companies; however, there is currently no federal oversight of the insurance industry. Instead, insurers are subject to state regulations, for example, to regularly contribute to state insurance guaranty funds. Interconnectedness between insurers within or between states can lead to the depletion of such funds, and further restrictions on the use of such guaranty funds and the lack of a federal supervisor and the lender of last resort can potentially lead to systemic fragility.

We propose a measure of interconnectedness among insurers based on the cosine similarity of their portfolios. The National Association of Insurance Commissioners (NAIC) requires that insurers disclose their portfolio holdings and transactions at the individual security level. Therefore, we are able to determine both the yearly portfolio composition and re-balancing through time. We demonstrate that our interconnectedness measure can predict asset liquidation at both the security issuer and at the asset class levels.

Using the sample of all insurers who file Schedule D, we show that their asset allocation decisions can be characterized by only a few different strategies. Cluster analysis reveals that insurer allocation strategies can be divided into three distinct strategies based upon the primary investment by the insurer: 1) corporate bonds, municipal bonds, and GSEs, 2) corporate bonds, and 3) equity.

[3]Ben S. Bernanke's May 10, 2013 speech "Monitoring the Financial System" at the 49th Annual Conference on Bank Structure and Competition sponsored by the Federal Reserve Bank of Chicago, Chicago, Illinois.

We find that broad asset allocation strategies among insurers tend to be long-term in nature and do not vary much over the business cycle.

Although broad asset class allocation strategies may remain similar through time, the actual composition of the portfolios may exhibit substantial variation either because the weights of the asset classes or the choice of individual securities within the strategy differ. Our methodology captures time-variation in the composition of insurer portfolios. To construct the cosine similarity between two insurers, we first construct a vector of portfolio weights for each insurer at the asset class or issuer (6 digit CUSIP) level. We then use cosine similarity to measure how similar are the portfolios of a pair of insurers.[4] Cosine similarity is easily interpreted because it is bounded between zero and one. The more similar the portfolios of two insurers, the closer the cosine similarity is to one and if two insurers' portfolios are completely different, the cosine similarity is zero.

We examine the determinants of pairwise portfolio similarity using a multivariate approach that controls for characteristics of the two insurers in a sample that consists of over 10 million insurer pair-years from 2002 to 2014. We show that for both asset class and issuer level similarity, two insurers have generally more similar portfolios if they are both in the same line of business (life or P&C). Life and P&C companies have different liability risks and thus, each will use portfolio allocation in different manner for risk management. Insurers are also more similar if their portfolios are less, not more, concentrated, as measured by a Herfindahl index. We interpret this finding to mean that diversification increases portfolio similarity. This is consistent with a growing literature (Castiglionesi and Navarro (2008), Wagner (2010), Ibragimov, Jaffee, and Walden (2011), Allen, Babus, and Carletti (2012), and Cont and Wagalath (2016)), which argues that diversification in the banking industry can lead to greater systemic risk because it leads banks to invest in similar assets.

We subset our analysis of insurer pairs into analysis of potential SIFIs (PSIFIs) and non-PSIFIs. We define a PSIFI as having $50 billion or more in consolidated assets in at least one year of our sample period.[5] At the asset class level, we find that pairs of insurers that are both PSIFIs and pairs of insurers that are both non-PSIFIs have greater portfolio similarity. At the issuer level, portfolio similarity continues to be greater when the pair of insurers are both PSIFI, but we do

[4]Sias, Turtle, and Zykaj (2016) also use cosine similarity to analyze hedge funds' trading behavior.

[5]This definition is similar to that used by the FSOC as a size threshold for nonbank SIFIs. The methodology for determining global systemically important insurers is also similar, see IAIS (2013) and IAIS (2015).

not have any evidence that non-PSIFI pairs are more likely to have higher portfolio similarities. In addition, the average level of portfolio similarity between pairs of PSIFIs is generally higher than the average portfolio similarity between pairs of non-PSIFIs throughout the sample period. Thus, we find preliminary evidence that the portfolios of PSIFIs are more likely to be composed of similar assets than the portfolios of other insurer pairs.

In order for our measure to be useful, it must predict the selling behavior of insurers. We use quarterly buy and sell transactions at the asset class and issuer levels to construct the cosine similarity of net sales (sales minus purchases). We find that the portfolio similarity of insurer pairs significantly predicts future sales similarity and this result holds for both PSIFIs and non-PSIFIs. Furthermore, if both insurers are large sellers (net sales to total holdings for the insurer is above the median for the sample), they have greater sales similarity and this relationship is intensified if the pair also has greater portfolio similarity. These findings suggest that commonality in portfolio holdings leads to commonality in portfolio rebalancing.

We also find that size is positively related to sales similarity. The size of insurers' business is likely to reflect the complexity of product lines and the propensity to engage in non-core insurance activities (e.g. securities lending, derivatives, reliance on reinsurance business etc.). Our result suggests that some unique aspect of insurers' business that is related to size may make them more susceptible to common shocks and hence prone to similar re-balancing decisions.

Other factors may influence selling behavior, most notably, capital regulation. The literature has shown that regulatory-capital constrained insurers attempt to improve their capital adequacy primarily by re-balancing their investment portfolios (Ellul, Jotikasthira, and Lundblad (2011), Ambrose, Cai, and Helwege (2008), Manconi, Massa, and Yasuda (2012)), and these activities can lead to fire sale prices (Merrill, Nadauld, Stulz, and Sherlund (2013)).[6]

We find that pairs of insurers with low risk-based capital (RBC) ratios (RBC in the bottom quartile of the sample) and similar portfolios are more likely to sell the same types of assets. However, a similar relationship also holds for pairs of insurers that have high RBC. Therefore, asset rebalancing is more correlated if both insurers have similar regulatory capital profiles. At the issuer level, however, only PSIFIs with low RBC ratios have greater sales similarity. The evidence at

[6] Chodorow-Reich, Ghent, and Haddad (2016) document that the equity prices of insurers do not fully reflect losses on the asset side of the balance sheet.

the issuer level is consistent with low regulatory capital creating incentives for correlated portfolio rebalancing among larger insurers.

Given a broad literature on the potential for regulated entities to sell liquid securities in times of crisis and to sell downgraded securities in order to avoid an increase in capital, it is possible that the relationship we document is driven by the re-balancing of insurers' portfolio in these types of securities and not more generally (or vice versa). We construct the portfolio similarity of liquid securities as those that fall within the following broad asset classes: equity, mutual fund shares, US government securities, GSE securities, and sovereign bonds. In a similar fashion, we construct the portfolio similarity of illiquid securities as those that fall within the following broad asset classes: corporate bonds, municipal bonds, RMBS, CMBS and ABS. The downgraded (not downgraded) portfolio similarity measure considers only issuers that are (are not) downgraded in the following year. We find that our results are not driven by the liquidity or changing credit quality of the portfolio of securities. Each of the four portfolio similarity measures significantly predicts subsequent sales similarity and these findings are not driven by low RBC insurers who have similar portfolios of credit-impaired or illiquid assets.

We also analyze whether our findings change in the period surrounding the financial crisis. We define three indicator variables, equal to one if the time period falls within 2002-2006 (*Pre-Crisis*), 2007-2009 (*Crisis*) and 2010-2014 (*Post-Crisis*), zero otherwise, and interact them with the portfolio similarities based on liquidity and downgrades. We do not find that the relationship between the portfolio similarity of illiquid and downgraded issuers and sales similarity is stronger during the financial crisis with the exception of the sample of PSIFIs. For PSIFIs, the effect of portfolio similarity on sales is greater for illiquid assets and downgraded issuers during the crisis and post-crisis periods. Therefore, pairs of larger insurers that may qualify for SIFI designation may be at greater risk of correlated selling if they both have similar holdings of downgraded or illiquid securities.

Next we examine whether public market information such as return correlation is related to sales similarity. A number of papers have proposed return correlation as a measure of interconnectedness (Billio, Getmansky, Lo, and Pelizzon (2012), Neale, Drake, Schorno, and Semann (2012), and Brunetti, Harris, Mankad, and Michailidis (2015)).[7] In order to examine whether market in-

[7] Karaca and Yilmaz (2016) use high-dimensional vector autogressions of daily stock return volatilities as a measure

formation can substitute for our measure of portfolio similarity in predicting sales similarity, we need to restrict our analysis to insurance holding companies that have equity returns on CRSP. We show that return correlation has no relationship to sales similarity at the asset class level but can predict sales similarity at the issuer level. Including portfolio similarity as an independent variable along with return correlation does not change our conclusions and portfolio similarity remains highly significant. These findings suggest that return correlation does not fully capture the effect of interconnectedness on the transmission of risk through the asset liquidation channel.

Finally, we propose an individual insurer-based metric, the average portfolio similarity with all other insurers, as a means to identify systemically important insurers. We show that this variable can provide additional information in predicting the insurer's contribution to overall selling over and above the size of the issuer at both the asset class and issuer levels. Furthermore, the average portfolio similarity remains significant after controlling for the total sales of the individual insurer. Thus, we propose that our metric can be used in tandem with other measures of potential systemic risk to identify candidates for SIFI designation.

Our analysis complements recent work on corporate bond herding among insurers. Chiang and Niehaus (2016) examine the herding behavior of life insurers and find that buy-side herding is more pronounced when insurers are part of groups that have been designated as SIFIs and the bond has been downgraded. Comparing mutual funds, pension funds and insurers, Cai, Han, Li, and Li (2016) also find evidence of herding by insurers in downgraded bonds. Our methodology provides a number of potential benefits over other measures of herding. First, our measure does not rely on an insurer having publicly traded equity and thus, can be used to understand the interconnectedness of private insurers. Second, the methodology does not rely on a small set of self-reported investment strategies that could be misleading. Cosine similarity allows for an objective and continuous measure of portfolio composition. Third, it can measure interconnectedness over a wide variety of asset classes, not just corporate bonds. Thus, regulators can use the method to delve deeper into the relationship between portfolio similarity and sales similarity at a more granular level, for example, in individual asset classes. Fourth, our method captures re-balancing across asset classes. For example, it is well-known that during the global financial crisis investors sold troubled assets and moved into safe assets such as Treasury securities. Last, our methodology

of interconnectedness.

allows for the possibility that insurers decide *not* to sell any particular securities. This is because sales similarity is based on insurer-triggered changes in portfolio holdings that may, in some cases, be zero.

Overall, our results indicate that the interconnectedness of insurers' portfolios, as measured by cosine similarity, captures attributes of interconnectedness that other simple measures such as portfolio concentration, return correlation, and size do not. More importantly, it also predicts commonality in asset liquidation across insurers making our measure relevant to regulators who are tasked with monitoring systemic risk in the economy.

The remainder of the paper is organized as follows. In Section 2 we present how our sample and variables are constructed as well as summary statistics. In Section 3 we describe the composition of insurers' portfolios using cluster analysis. In Section 4 we define our pairwise cosine portfolio similarity measure and investigate its determinants. Section 5 presents our examination of the relationship between portfolio similarity and sales similarity including how capital constraints, liquidity, downgrades, and the financial crisis affect our findings. We propose our individual insurer metric in Section 6. We conclude in Section 7.

2 Data

We analyze the portfolio interconnectedness of insurers from 2002 to 2014 using information from their statutory filings with the NAIC as distributed by A.M. Best. Parts 1 and 2 of Schedule D list for each insurer the par value and book value of each security held at calendar year-end. We retain annual holdings data with non-negative reported positions. Disposals and acquisitions of securities are reported in Parts 3, 4 and 5 of Schedule D. For each insurer, the data includes every security disposed of or purchased during the year along with its par value, disposal/purchase value, and date of disposal/purchase. We exclude any security disposal due to maturity, repayment, calls, or other non-trading activity. We use this data to construct quarterly net sales as sales minus purchases during the quarter.[8]

Both portfolio holdings, sales and purchases are reported at the individual security (9-digit CUSIP) level. For each insurer, we aggregate this information to the security issuer or the asset

[8] We only consider non-negative net sales.

class level.[9] To aggregate holdings and net sales to the issuer level, we use the first 6 digits of each CUSIP as the issuer identifier and aggregate every security with the same 6 digit CUSIP by summing all holdings and sales.[10]

To aggregate holdings to the asset class level, we categorize each security into one of 34 asset classes as follows. First, we categorize each security into one of ten broad categories: (1) U.S. government debt, (2) GSE debt (including mortgage-backed securities), (3) municipal debt, (4) sovereign debt, (5) corporate debt, (6) private-label RMBS, (7) private-label CMBS, (8) private-label ABS, (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.[11] We classify all other types of 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. If we are unable to categorize a security using this algorithm, we assign it to the asset class its holder reports in Schedule D. Second, we refine our classification of equity, municipal securities and corporate securities using the issuer's industry or sector information reported in Schedule D. This results in the 34 asset classes listed in Appendix A.

Schedule D is filed by each individual insurer. However, the predominant organizational structure in the insurance industry is the insurance group. Although in many ways individual companies operate independently, some aspects of their operations are centrally managed thus creating strong connections among the members of a group. We, therefore, conduct the majority of our analysis at the group rather than the individual insurer. To do so, we aggregate holdings, net sales and balance sheet information to the group level, which results in a sample of 2,812 different insurance groups. We refer to these as "insurers" in the rest of the paper.

For some of our analysis, we require stock return data, which is only available at the holding

[9]When aggregating, we use the par value of fixed-income holdings. Since no comparable number exists for equity securities, we aggregate equity using book value.

[10]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.

[11]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 (2015).

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 CRSP/Compustat Merged and are able to find matches for 73-99 (depending on the calendar year) insurer groups. For each holding company, we calculate portfolio similarity between holding companies and collect daily holding period returns from CRSP.

We also categorize insurers as P&C, life, or other (e.g. health, fraternal, and title) if at least half of the insurers' portfolio assets are held in a given year by companies in the group that are in that line of business.[12] The majority of the insurers in the sample are P&C companies (1,746) as opposed to life (635). In order to examine whether systemically important insurers are more likely to have similar portfolios, we classify insurers as Potentially Systemically Important Institutions (or PSIFIs) if they have more than $50 billion in total assets in at least one year of the sample. Based on this size threshold, we identify 38 insurers as potential candidates for SIFI designation by the FSOC.[13] Appendix B provides detailed definitions of all of the variables used in our analysis.

2.1 Sample Characteristics

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

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 the majority of their holdings with more than 81% on average. Corporate bonds (27%), GSE securities (19%), municipal bonds (14%) and U.S. government secu-

[12] The number of insurers in the "other" category is small and we do not report summary statistics separately for this type. Therefore, the sum of Life and P&C insurers do not add up to the total number.

[13] 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 from the balance sheet, which is not available for all insurers in the sample.

rities (15%) represent the largest proportion of insurers' fixed-income investments in our sample. Equity holdings of insurers 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 total holdings. Finally, there appears to be significant cross-sectional variation in asset class holdings across insurers as indicated by the standard deviation.

Figure 1 summarizes the time-series variation of our sample of insurers' cross-sectional holdings and indicates that shifts in and out of asset classes occur through time. Over our sample period, the proportion of the portfolio allocated to U.S. government and ABS securities increases. 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 (2015).

The average insurer in our sample holds 380 different securities issued by 250 separate issuers. The median number of securities (issuers) held is less than half of the sample average, implying that some insurers invest in significantly more securities than others. Table 1 shows that some of this variation in holdings by asset class is related to insurer type. Life insurers invest in more securities and issuers than P&C insurers, and their portfolios are more heavily weighted toward corporate bonds and asset-/mortgage-backed securities, and less toward municipal bonds and equity.

We also separately examine the portfolio composition of PSIFI and non-PSIFI insurers. PSIFIs hold an average of 3,704 different securities issued by 1,888 issuers compared to the non-PSIFI mean of 223 securities issued by 172 issuers. PSIFIs invest a greater proportion of their portfolios in corporate bonds than non-PSIFIs, and very little in other types of asset classes. Non-PSIFIs have more balanced portfolios that are almost equally allocated to GSE securities, municipal bonds, US government securities, and equity.

We measure the level of portfolio concentration at both the asset class and issuer level using a Herfindahl index. Specifically, asset class portfolio concentration is:

$$Concentration\_AC_{i,t} = \sum_{k=1}^{K} w_{i,k,t}^2 \tag{1}$$

where $w_{i,k,t}$ is the asset class k weight for an insurer i and is calculated as the dollar amount invested in asset class k relative to the total value of the insurer i portfolio at the end of year t.

Similarly, issuer-level concentration is:

$$Concentration\_I_{i,t} = \sum_{n=1}^{N} w_{i,n,t}^2 \tag{2}$$

where $w_{i,n,t}$ is issuer n weight for an insurer i and is calculated as the dollar amount invested in issuer n relative to the total value of the insurer i portfolio at the end of year t.

Table 1 reports the cross-sectional mean, median and standard deviation of insurers' time-series averages of the two concentration measures. The average asset class concentration in our sample is 0.31 and the average issuer concentration is 0.16. Life and P&C insurers have similar portfolio concentrations. Finally, PSIFIs' portfolios are less concentrated than those of non-PSIFIs at both the asset class and issuer level indicating that PSIFIs' portfolios are more diversified.

3 Portfolio Composition Using Cluster Analysis

In this section, we examine the portfolio strategies of insurers at the asset class level using cluster analysis.[14] We are interested in 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 are likely to have closer connections with each other than with those outside the cluster. As shown in Appendix C, the cluster validation process produces three distinct clusters suggesting that firms in the insurance industry employ only a small number of portfolio strategies.

The average structure of the three clusters is displayed in Figure 2. Cluster 1 of the sample is diversified across our broad asset classes. Cluster 2 is mainly invested in corporate bonds and GSE securities. Cluster 3 is dominated by equity. In terms of the number of insurers in each cluster, Cluster 1 and Cluster 2 are evenly split with approximately 45% of the sample of all insurers in each cluster. The remaining 10% of insurers are in Cluster 3. If we apply the cluster analysis separately in each year, the optimal number of clusters remains at three and the composition of each cluster is relatively stable.[15]

[14] Blei and Ergashev (2014) use cluster analysis to construct ACRISK, a measure of systemic risk based on commonalities in bank's asset holdings that captures the buildup of systemic risk.

[15] In unreported results, we find that insurers infrequently move between clusters.

Figure 3 shows the distribution of PSIFIs and non-PSIFIs in each cluster. There is a clear distinction for portfolio allocations done by PSIFIs vs. non-PSIFIs. PSIFIs portfolios mostly resemble Cluster 2 which is dominated by corporate bonds and GSE securities. However, non-PSIFIs portfolios are dominated by Cluster 1 which is more diversified across different broad asset classes. These results are consistent with results in Table 1. The different portfolio strategies employed by PSIFIs and non-PSIFIs highlights the potential for important differences in rebalancing behavior during times of stress.

The cluster analysis of insurer portfolios suggests that insurers are very similar in their asset composition and therefore, potentially in their trading strategy. Unlike mutual funds, which the literature suggests follow a large number of portfolio strategies, insurers appear to follow only a few. In the next section, we discuss a methodology that captures the granularity of portfolio choices among insurers.

4 Portfolio Similarity

In order to determine whether insurers with comparable portfolios are likely to trade in a related fashion, we construct a measure of portfolio similarity using cosine similarity. Cosine similarity is well-suited to comparing the "distance" between two vectors and in economics, has been more recently used in text analytics (Hanley and Hoberg (2010) and Hanley and Hoberg (2012)) and hedge fund portfolio analysis (Sias, Turtle, and Zykaj (2016)).

To construct cosine similarity, we first calculate the proportional dollar value of each asset class or issuer of securities held in an insurer's portfolio at the end of each year. We then create a vector of portfolio weights. For example, the maximum number of unique issuers in a given year is approximately 32,000 and therefore, each insurer's portfolio of issuers has a vector length of 32,000. If an insurer does not invest in a particular issuer in a given year, the weight is set to 0. We perform an analogous vector weighting for the 34 asset classes.

To measure the degree of similarity between insurers i and j in year t, we calculate the cosine similarity as the dot product of the pair's portfolio weight vectors normalized by the vectors' lengths. We refer to this quantity as $Similarity_{i,j,t}$ and calculate it using portfolio weights based on either asset class or issuer.

$$Similarity_{i,j,t} = \frac{\boldsymbol{w_{i,t}} \cdot \boldsymbol{w_{j,t}}}{\|\boldsymbol{w_{i,t}}\| \; \|\boldsymbol{w_{j,t}}\|} \tag{3}$$

Because all portfolio weight vectors have elements that are non-negative, this measure of portfolio similarity has the property of being bounded in the interval (0,1). Intuitively, the portfolio similarity between two insurers is closer to one when they are more similar and can never be less than zero if they are entirely different.

Figure 4 shows the time series of the average pairwise similarity at the asset class and issuer level for the sample of all insurers and for the subsamples of PSIFI pairs (*PSIFI_Pair*) or non-PSIFI pairs (*Non-PSIFI_Pair*). Since non-PSIFIs make up the majority of the insurers in our sample, their average portfolio similarity closely mimics that of all insurers at either the asset class or issuer level. PSIFI pairs have higher asset class and issuer similarity than non-PSIFI pairs. PSIFIs' asset class similarity does not fluctuate much over time, while that of non-PSIFIs decreases. At the issuer level, non-PSIFIs' portfolio similarity is relatively constant while PSIFIs have become more similar over time. Interestingly, the divergence in portfolio similarity for PSIFIs relative to non-PSIFIs increases after the financial crisis.

4.1 Determinants of Portfolio Similarity

To gain a better understanding of the determinants of pairwise portfolio similarity, we examine the relationship between *Similarity* and insurer-pair 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 equals 1 if both insurers are life (*Life_Pair*) or P&C (*PC_Pair*), and 0 otherwise. We define a large insurer as one with portfolio assets above the median and create indicator variables equal to 1 if both insurers are large (*Big_Pair*) or small (*Small_Pair*), 0 otherwise. We also consider the asset class or issuer concentration of an insurer's portfolio and define it as high (low) if it is above (below) the median for the sample. We then construct two pairwise indicator variables at either the asset class (*AC*) or issuer (*I*) level that equal 1 if both insurers in the pair have portfolios with high (*Conc_Pair*) or low (*NonConc_Pair*) concentration, 0 otherwise.

We estimate OLS regressions where the dependent variable, $Similarity_{i,j,t}$, is the pairwise holdings similarity measure in a given year defined at either the asset class (Models (1) - (3)) or issuer level (Models (4) - (6)). Table 2 presents the regression results. When we examine the determinants of asset class portfolio similarity for all insurers in Model (1), we find that the similarity between two insurers is greater if they are in the same line of business. Life and P&C insurers have very different liability and risk structures such as life, catastrophe, hurricane, and other risks that are unique to each line of business. Insurers will try to match asset risk and thus portfolio allocation decisions to their different liability structures. As a result, it makes sense for insurers in the same line of business to have similar portfolios.

Portfolio holdings similarity between two insurers is greater if insurers have the same PSIFI classification. This means that when both insurers in the pair are either both PSIFIs or non-PSIFIs, they have more similar portfolio holdings than pairs in which one insurer is a PSIFI and the other is a non-PSIFI. We also find that if two insurers are not concentrated at the asset class level, i.e., have more diversified asset class holdings, they have higher portfolio holdings similarity. Recent theoretical works have shown that full diversification may not be optimal from a systemic risk perspective because it can lead to financial contagion. For example, a number of papers such as Allen, Babus, and Carletti (2012), Castiglionesi and Navarro (2008), Ibragimov, Jaffee, and Walden (2011), Wagner (2010)), Ibragimov, Jaffee, and Walden (2011), Wagner (2010), and Beale, Rand, Battey, Croxson, May, and Nowak (2011) show that even though diversification of assets reduces each institution's individual probability of failure, it can make systemic crises more likely.

Examining portfolio similarity at the issuer level in Model (4) we find different relationships. If two insurers are P&C insurers, they are more similar in their portfolio holdings but life pairs are not. As with the results on asset class level, PSIFI pairs of insurers have greater portfolio holdings similarity while non-PSIFI pairs are lower. Unlike the relationship at the asset class level, concentrated pairs have greater and non-concentrated pairs have lower holdings similarity.

We split the sample of insurers into PSIFI pairs and non-PSIFI pairs (all pairs of firms that include one PSIFI and one non-PSIFI are in the intercept) in Models (2), (3), (5) and (6), to examine whether the determinants of similarity differ within these categories. At the asset class level, the results for both PSIFIs and non-PSIFIs are similar to the results for all insurers. For non-PSIFIs, we find some evidence that larger, but not smaller pairs of non-PSIFIs have greater portfolio similarity. Thus, larger insurer pairs are more similar to each other regardless of SIFI status. Larger insurance companies are more likely to engage in non-core insurance activities and have more complex product lines, and thus are more likely to be affected by a similar shock.

When we consider the issuer level of portfolio similarity, we find that the relationships for non-PSIFIs echoes that of the full sample. For PSIFIs, however, life but not P&C pairs are more similar. In terms of concentration, PSIFIs are always more similar if they are more diversified. Non-PSIFIs are more similar when they hold the same issuers and this may be due to the propensity for smaller insurers to invest in more well-known, liquid issuers and draw from the same pool of advisors for their portfolio construction.

Overall, the findings of this table point to the important role that size and business lines plays in the similarity of portfolio holdings. Correlated holdings of securities may lead to correlated re-balancing in times of stress. Next, we examine whether holdings similarity can predict sales similarity.

5 Portfolio Similarity and Asset Liquidation

In order to examine whether insurers that are more similar are more likely to trade either the same asset class or issuer, we construct a measure of sales similarity, $Sales\_Similarity_{i,j,q}$ between insurers i and j in quarter q using the cosine similarity methodology described earlier. For each insurer, we create a vector of quarterly net sales (sales-purchases) weights as a proportion of the insurer's total sales of each asset class or issuer of securities in the prior quarter. If an insurer does not sell assets in a particular asset class or sell securities issued by an issuer, the weight of the element is set to 0.[16]

Figure 5 presents the times series of quarterly sales similarity for the sample of insurers as well as for PSIFIs and non-PSIFIs at the asset class and issuer levels. There is a great deal of variation in the similarity in portfolio sales over the sample time period, particularly for PSIFIs. At the asset class level, PSIFIs have greater sales similarity, in general, with some volatility particularly during the financial crisis. When we define sales at the issuer level, PSIFIs always have greater sales similarity than non-PSIFIs but interestingly, the sales similarity at the issuer level declines during the financial crisis. The figure provides preliminary evidence to support regulators' concerns

[16] If an insurer does not sell anything at all during the quarter, we cannot compute the cosine similarity with other insurers because all of the vector weights are zero. Therefore, these insurers would not be included in our tests.

about correlated trading behavior in PSIFIs.

In Table 3, we investigate the determinants of sales similarity. We predict that insurers with more similar portfolios will sell similar asset classes and issuers as suggested by the theoretical work of Allen, Babus, and Carletti (2012). Specifically, we estimate OLS regressions of quarterly sales similarity on the prior year portfolio holdings similarity constructed at the issuer or asset class levels. We control for other pair characteristics and include year-quarter fixed effects.

The findings of Table 3 are consistent with our prediction. At both the asset class and issuer level in Models (1) and (4), we find a significant relationship between the similarity in portfolio holdings and the similarity in asset sales. Pairs of insurers that have more similar portfolios are more likely to sell similar assets. We investigate whether this relationship is stronger for pairs that are selling more assets by creating an indicator variable, *High_Sales*, equal to 1 if, during a given quarter, each insurer in the pair is selling above the overall median ratio of $netsales_t/holdings_{t-1}$ for all insurers. Sales similarity is higher when both pairs have high sales. When interacted with portfolio similarity, we show that insurer pairs have greater sales similarity when they hold similar assets and are both active sellers.

In addition to portfolio similarity, other insurer characteristics may be useful in predicting sales similarity. P&C insurer pairs but not life insurer pairs tend to have greater sales similarity at the asset class level but lower sales similarity at the issuer level. If both pairs have non-concentrated portfolios, they tend to sell the same asset classes. At the issuer level, the relationship is negative mirroring the findings on the determinants of portfolio similarity. Although concentration has been proposed as a potential metric to identify systemically important financial institutions (Haldane and May (2011) Gai, Haldane, and Kapadia (2011) and Allen, Babus, and Carletti (2012)), our results suggest, along with the prior table, that concentration measures may not fully capture the effect of portfolio similarity on asset sales.

When examining whether PSIFI pairs have greater similarity for the sample of all insurers, we find that regardless of the type of sales similarity examined, *PSIFI_Pair* is positively significant and *Non-PSIFI_Pair* is negative. Examining PSIFIs and non-PSIFIs separately, we find that if the non-PSIFI pair is large, they have greater sales similarity. This finding points to the potential for correlated asset liquidation for larger insurers. This means that both potentially systemic insurers and relatively large non-systemic insurers tend to sell similar issuers but smaller non-systemic insurers do not. Thus, size is capturing a unique aspect of insurers' business that is indicative of their likelihood to make similar selling decisions. The size of their business, for instance, is likely to reflect the complexity of product lines and the propensity to engage in non-core insurance activities (e.g. securities lending, derivatives, reliance on reinsurance business etc.). Additional research is warranted to better understand the underlying economics of the contribution of size that could result in common rebalancing decisions.

Overall our findings confirm that portfolio similarity is an important determinant of sales similarity and this relationship is strengthened when both insurers sell more assets. Thus, our measure of portfolio interconnectedness appears to capture information about future sales that could be used to monitor insurers who may contribute more to the transmission of systemic risk through the asset liquidation channel. Next, we examine whether these relationships may be driven by insurers with low regulatory capital.

5.1 Risk-Based Capital Ratios

Entities subject to capital regulation have an incentive to engage in asset sales when capital is depleted. The literature has documented that insurers replenish capital by selling downgraded assets (Ellul, Jotikasthira, and Lundblad (2011)) and/or selling liquid assets (Ellul, Jotikasthira, Lundblad, and Wang (2015)). In this section, we examine whether our findings on the relationship between portfolio similarity and sales similarity are due to 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 larger RBC ratio can potentially reduce the extent of fire sales and provide a buffer for asset sales. We consider an insurer under-capitalized if its RBC ratio is at or below the first quartile of the RBC of all insurers and well-capitalized if the RBC ratio is above the first quartile.[17] We then construct two pairwise indicator variables, (*RBC_High_Pair*) and (*RBC_Low_Pair*), equal to one if both insurers are well-capitalized or under-capitalized, respectively.

If our results are driven by the selling behavior of pairs of insurers that are capital constrained and who have similar portfolios, then we would expect that the interaction term between portfolio similarity and low RBC, *Similarity*RBC_Low_Pair*, to be positive and significant. The results in

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

Table 4 presents evidence on the interaction effect of regulatory capital constraints and portfolio similarity on sales similarity. At both the issuer and asset class levels in all models, insurer pairs that have low RBC and similar portfolios are not more likely to sell similar assets. The interaction term between portfolio similarity and low RBC in Model (1), however, is significant for sales at the asset class but not the issuer level. Interestingly, pairs of insurers with more similar portfolios that have *high* RBC are also more likely to sell similar assets. Thus, capital adequacy or constraints affect the selling behavior of insurers who have similar portfolios. At the issuer level in Model (4), we do not find any effect of RBC interacted with portfolio similarity. One interpretation of this finding is that insurers who have similar RBC profiles and high portfolio similarity are likely to trade similar asset classes but not necessarily similar issuers.

When the sample is split between PSIFIs and non-PSIFIs, we find significance on the coefficient of the interaction term between portfolio similarity and low RBC ratio for non-PSIFIs at the asset class level (Model (2)) and for PSIFIs at the issuer level (Model (6)). This suggests that PSIFIs may be liquidating the same issuers when they need to replenish capital while non-PSIFIs tend to rebalance within broader asset classes. The findings on PSIFIs also highlights the potential for low regulatory capital to play a role in larger, potentially systemic insurers.

Overall, this subsection suggests that there is a stronger relationship between portfolio similarity and asset class sales similarity when both pairs of insurers have inadequate capital. Next we examine whether our findings are driven by either the liquidity of the assets or downgraded securities.

5.2 Liquidity and Downgrades

In this section, we test whether the similarity in portfolio holdings of illiquid or downgraded assets has the potential to be disruptive to markets, particularly for regulated entities if they need to replenish capital. In terms of liquidity, if the similarity of selling behavior among insurers is due to the similarity in their portfolios of illiquid assets, regulators may be concerned about forced selling and price impact. Such interconnected insurers will have a larger impact on prices and increase the probability of a downward spiral in valuations (Brunnermeier and Pedersen (2009), and Cont and Wagalath (2015)).

Our determination of liquidity is conducted at the broad asset class level. We classify the holdings of insurers in each asset class as being liquid if they are the following broad asset classes:

equity, mutual fund shares, US government securities, GSE securities, and sovereign bonds. Asset classes that are considered illiquid are corporate bonds, municipal bonds, RMBS, CMBS and ABS. We then deconstruct the portfolio similarity between two issuers into those broad asset classes that are classified as liquid, *Similarity_AC_Liquid*, and illiquid, *Similarity_AC_Illiquid*.

A similar logic to the one discussed above regarding liquidity prevails with respect to the effect of downgraded assets. A number of studies document that asset sales of distressed securities by capital constrained insurers tend to depress prices (Ellul, Jotikasthira, and Lundblad (2011) and Merrill, Nadauld, Stulz, and Sherlund (2013)) and help to explain why some insurers have been designated as systemically important. Thus, it could be the case that the relationship between portfolio similarity and sales similarity is simply due to the portfolio similarity in downgraded assets. We explore this hypotheses in the following analysis.

Our determination of credit quality is conducted at the issuer level. Using credit ratings information from DataScope, we identify the year in which a security is first downgraded from investment grade (IG) to non-investment grade (NIG) by S&P, Moodys or Fitch. This information is aggregated to the security's issuer level and we define a downgraded issuer as one that has at least one of its securities downgraded from IG to NIG in a given year. For portfolio holdings similarity, we deconstruct the portfolio similarity of pairs of issuers into *Similarity_I_Downgraded* as the portfolio similarity of issuers downgraded in the following year and *Similarity_ I_NotDowngraded* as the portfolio similarity for issuers that are not downgraded in the following year.

Figure 6 shows the proportion of the portfolio holdings and sales that are comprised of illiquid issuers and downgraded securities. In Panel (a), approximately 70% of insurers holdings are composed of securities that we consider illiquid and this is relatively constant over the time period. Panel (b) shows a significant time trend in the percentage of insurers holdings that are downgraded securities with the peak during the financial crisis. The changes in portfolio composition based on credit quality, in particular, points to the possibility that sales similarity may be affected by only a portion of an insurer's portfolio.

Table 5 presents the analysis of the relationship between the decomposition of portfolio similarities based on liquidity, credit quality, and sales similarities. As can be seen from the table, neither liquidity or credit quality are driving our results. The coefficients on each of the decomposed portfolio similarities: liquid, illiquid, downgraded, and not downgraded, are highly significant and positive. We interpret this relationship to mean that the sales similarity of a pair of issuers is affected by the portfolio similarity of all securities in the portfolio and not just those that have lower liquidity or lower credit ratings.

It is possible, however, that insurer pairs with similar portfolios of illiquid or downgraded securities are more likely to sell the same asset class or issuer when both insurers need to rebuild capital. To test this theory, we interact our decomposed portfolio similarity measures with *RBC_High_Pair* and *RBC_Low_Pair*. If regulatory capital depletion is the reason for selling downgraded or illiquid securities, we expect to find that the coefficient on the interaction term between illiquid and downgraded portfolio similarity and low RBC will be positive and significant. In Model (1), we find weak evidence that insurers with similar portfolios of illiquid securities and low capital have higher sales similarity. But this is also true for high RBC insurers that hold similar illiquid assets. Furthermore, insurer pairs with low RBC and greater similarity in their holdings of liquid assets are also marginally more likely to sell them. For downgraded securities in Model (4), we find little evidence that insurers are more likely to have high sales similarity when they hold similar portfolios of distressed securities and they have low RBC. Overall, the results of this section suggest that neither liquidity nor credit quality is driving our results. We next explore whether the portfolio similarity and sales similarity relationship changed during the financial crisis.

5.3 The Financial Crisis

Given the concern about the selling behavior of regulated entities during the financial crisis, it is natural to examine whether our findings are due only to this time period. We consider three different time periods and create dummy variables equal to 1 if the time period falls within: (1) *Pre-Crisis* from 2002-2006, (2) *Crisis* from 2007 to 2009, and (3) *Post-Crisis* from 2010 to 2014. We interact two of these measures, *Crisis* and *Post-Crisis* with portfolio similarity using liquid/illiquid assets and issuers that are downgraded/not downgraded.

In Table 6, the coefficient on *Crisis* indicates that sales similarity at the asset class level in Model (1) is lower, not higher during the crisis and this relationship continues to hold post-crisis as well. At the issuer level in Model (4), there is no effect of the crisis period on sales similarity but a positive coefficient in the post-crisis period. Therefore, insurers' sales similarity appears to be higher after the crisis.

We also include interaction terms of portfolio similarity based on liquidity and credit quality and *Crisis* and *Post-Crisis*. During the crisis, pairs of insurers that have high portfolio similarity of liquid but not illiquid asset classes have greater sales similarity. This result indicates that any price pressure that could occur as the result of correlated selling in insurers will occur in liquid, not illiquid assets. Khandani and Lo (2007) show that many quantitative long/short equity funds with relatively liquid strategies lost money due to having correlated portfolios during the financial crisis.

After the crisis, the portfolio similarity of both liquid and illiquid asset classes predicts sales similarity. For the sample of all insurers and non-PSIFIs, we do not find a stronger relationship between the portfolio similarity of downgraded issuers and sales similarity during the crisis or afterwards.[18]

Concerns about correlated trading in illiquid and downgraded securities for PSIFIs, however, appear to be validated in Table 6. During the financial crisis, PSIFIs with greater portfolio similarity of illiquid and downgraded securities have higher sales similarity and these relationships still remain strong even after the crisis ends. This finding could be because PSIFIs may have sustained the largest percentage of downgrades to their portfolios during the crisis. If that is the case, then it is natural to think that these insurers would actively dispose of downgraded issuers. Hence, for PSIFIs, the relationship between holding similarity and sales similarity would have been driven by the downgraded portion of their portfolios.

5.4 Return Correlation and Sales Similarity

In this section, we examine whether portfolio similarity can be captured by public market information such as return correlation. For example, Billio, Getmansky, Lo, and Pelizzon (2012), Neale, Drake, Schorno, and Semann (2012), and Brunetti, Harris, Mankad, and Michailidis (2015) use return correlation as a measure of interconnectedness for insurance and interbank markets. This analysis is important because market-based measures of interconnectedness for other types of nonbank financial companies that may contribute to systemic risk, such as hedge funds, is not

[18] This does not mean that insurers did not sell more during the crisis, it only means that the relationship between holdings and sales did not change. For example, Figure 6 indicates that sales of downgraded securities increased in 2009.

readily available but portfolio similarity may be (Sias, Turtle, and Zykaj (2016)).[19] The advantage of using a market-based measure of interconnectedness like return correlation is that it is easy to compute. However, return correlation may not capture the full extent to which insurers are connected through their portfolio strategies.

As noted previously, equity returns are only available at the holding company level. Although we restrict our analysis in this section to holding companies, the aggregation of insurers to the holding company level accounts for 68-76% of the book value of Schedule D holdings reported by all insurers. Although our tests are limited to these insurers, the findings apply to most of the asset value of the insurance industry.

In order to determine whether the pairwise correlation of stock returns (*RetCorr_Pair*) is a good proxy for a pair of insurers' portfolio similarity, we include the return correlation between a pair of issuers in the quarter before sales similarity is measured as the independent variable of interest. We find no relationship between *RetCorr_Pair* and sales similarity at the asset class level in Model (1), after adjusting for the pair's portfolio concentration, size, and line of business. Including portfolio similarity in the set of independent variables does not change the result of no relationship between *RetCorr_Pair* and sales similarity, and our portfolio similarity measure continues to remain significant.

At the issuer level, we find greater predictability of return correlation with sales similarity. Including portfolio similarity, however, dramatically increases the R^2 (from 2.9% in Model (5) to 19.3% in Model (6)) and the significance of the coefficient on return correlation is only present for non-PSIFIs. Thus, we conclude that this market-based indicator of connectedness is not a good predictor of sales similarity for the largest, potentially systemic insurers.

Overall, the findings in this section indicate that a market-based measure of interconnectedness such as the correlation of insurers' equity returns does not capture sales similarity well. This is likely due to the fact that equity correlation between insurers reflect many different aspects of insurer pair's balance sheet and operations of which portfolio sales is one characteristic. Using return correlation alone to predict asset liquidation for insurers and possibly other portfolio managers may be problematic. Below we investigate whether our portfolio similarity measures contain information

[19] See Ben Bernanke, in his speech to the Federal Reserve Bank of Atlanta in 2006 discussing the systemic risk of hedge funds http://www.federalreserve.gov/newsevents/speech/bernanke20060516a.htm.

about future asset liquidation.

6 Individual Insurers

In order for regulators to engage in prudential supervision of potentially systemic insurers, they must have the ability to identify specific entities that may contribute to the asset liquidation channel in times of stress. We propose a methodology that transforms the relationship of insurer pairs into a metric of connectedness at the individual insurer level. Using the sample of insurance holding companies, we compute the average portfolio similarity of an individual insurance holding company with all other insurance holding companies.

We predict that insurance companies that have greater average portfolio similarity will sell more in common with all other insurers. To test this in Table 8, we use as our dependent variable for insurer i, the log sum of all the pairwise insurer's i dot products of net dollar sales with the other $N-1$ companies, at both the asset class and issuer levels for quarters Q1 to Q4 in year $t+1$. This dollar sales similarity measure captures individual insurer's commonality of sales with all other insurers. It is important to note that dollar sales similarity is based on dollar sales amounts and is not normalized by holdings or total sales. In this way, we make sure that our results are not driven by small sales (that might have larger normalized sales fractions) and instead are capturing the total impact of average portfolio similarity on total sales similarity for each insurer. Our main independent variable of interest is the average portfolio similarity at the asset class or issuer level of insurer i with all other *N-1* insurance companies (*Similarity_Avg*).[20]

We also include as independent variables: *Ln(TotalSales)* defined as the log size of the net sales of insurer i, at both the asset class and issuer level, *Ln(Size)* defined as the log size of the portfolio of insurer i, *Similarity_Avg_BusLines* measured as the simple average similarity between the business lines of insurer i and those of the other $N-1$ insurers and *Conc* is the concentration of insurer i's holdings, at the asset class and issuer level. All independent variables are measured as of the year-end prior to the sales quarter.

The results in Table 8 indicate that *Similarity_Avg* can predict dollar sales similarity for a

[20] *Similarity_Avg* has similarities to Cont and Schaanning (2016)'s Indirect Contagion Index (ICI). Using portfolio holding data for European banks from EBA stress tests, they find a significant and positive relationship between fire sales losses and ICI.

given insurer both at the asset class and issuer levels. The regression coefficient on this variable is significant for all models except for Model (1). The regressions also show that both the size of sales and the size of the insurer are relevant variables in predicting dollar sales similarities. Larger insurers that sell more securities have greater pairwise total dollar sales. In conclusion, our results suggest that the average portfolio similarity of an individual insurer conveys additional information over and above other metrics such as size and trading that could be used to identify systemically important nonbank institutions. Therefore, it might be imperative for regulators to rank insurers based on the average portfolio similarity, as such a ranking can be used to predict total sales in common with all other insurers, and thus help to identify asset liquidation channel vulnerabilities.

7 Conclusion

The Financial Stability Oversight Council (FSOC) has an authority to designate nonbank Systemically Important Financial Institutions (SIFIs). Size and interconnectedness between financial companies are two factors the FSOC currently considers in the designation process and these characteristics are assumed to affect the asset liquidation channel. However, there is little guidance on how to measure interconnectedness. In this paper, we develop a novel measure of pairwise interconnectedness that focuses on insurance company portfolio similarities and examine its contribution to selling behavior.

Our findings show that pairs of insurers that have greater portfolio similarity will have greater sales similarity at both the asset class and issuer levels and this result holds when both pairs are potential SIFIs (PSIFIs) and non-PSIFIs. Portfolio re-balancing for insurers with similar portfolios is more likely when both insurers are heavy sellers of securities and in some cases, when the insurer pair are both capital constrained. We find that both the portfolio similarity of liquid and illiquid securities as well as downgraded and non-downgraded issuers predict sales similarity.

The similarity in holdings of illiquid and downgraded assets, particularly during and after the crisis, is significantly related to sales similarity but only for those insurers that are hypothesized to contribute the most to systemic risk, PSIFIs. Thus, our findings provide additional evidence that larger insurers may contribute to the asset liquidation channels related to liquidity and credit quality. In addition, we show that our measure of interconnectedness and its relationship to selling behavior is not captured by market observable characteristics such as stock return correlation.

Finally, we use the average portfolio similarity with all other insurers as a metric to gauge the potential for an individual insurer to contribute to the systemic risk through the asset liquidation channel. We show that while both size and selling intensity affect the combined sales of an insurer with all other insurers, our measure of portfolio similarity is incrementally important in predicting the level of correlated selling.

Overall, our results support the use of our measure to capture the important mechanics of the asset liquidation channel in the insurance industry. Specifically, it can predict the sales of similar assets and issuers. The measure can be used by insurance companies and regulators to assess the level of interconnectedness in the insurance industry and the possible impact of interconnectedness on asset liquidation.

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Appendix A: Asset Classes

US_Govt
Mutual_Funds
Equity_Utilities
GSE
Equity_Services
Equity_Energy
Sovereign
Equity_Undefined
Equity_Technology
Equity_Health
Debt_Technology
Equity_Basic_Materials_Durable
Debt_Health
Muni_Revenue
Equity_Pharma_Chemical
Equity_Consumer_Staples_Retail
Debt_Services
Debt_Pharma_Chemical
Debt_Undefined
Debt_Financials_Undefined
Debt_Basic_Materials_Durables
Debt_Banks
Equity_Banks
Debt_Consumer_Staples_Retail
ABS
Debt_Insurers
Debt_Energy
Equity_Financials_Undefined
Muni_GO
Equity_GSE
RMBS
CMBS
Debt_Utilities
Equity_Insurers

Appendix B: Variable Definitions

Variable	Definition
Big	An indicator variable equal to 1 if a non-PSIFI insurer's portfolio assets are above the sample median at calendar year end, 0 otherwise.
Big Pair	An indicator variable equal to 1 if Big=1 for both insurers in a pair, 0 otherwise.
Concentration	Issuer/Asset Class level Herfindahl index of an insurer's portfolio at calendar year end: $Concentration_{i,t} = \sum_{n=1}^{N} w_{i,n,t}^2$ where $w_{i,n,t}$ is issuer/asset class n's proportion in insurer i's portfolio at the end of year t. Issuer/Asset Class level proportions are calculated as the dollar amount invested in each issuer/asset class relative to the total value of the insurer portfolio.
Conc_Pair_I	An indicator variable equal to 1 if Conc_I=1 for both insurers in a pair, 0 otherwise.
Conc_Pair_AC	An indicator variable equal to 1 if Conc_AC=1 for both insurers in a pair, 0 otherwise.
Conc_I	An indicator variable equal to 1 if an insurer's issuer concentration is above the sample median at calendar year end, 0 otherwise.
Conc_AC	An indicator variable equal to 1 if an insurer's asset class concentration is above the sample median at calendar year end, 0 otherwise.
Crisis	An indicator variable equal to 1 for the years 2007, 2008, and 2009, 0 otherwise.
High_Sales	An indicator variable equal to 1 if each insurer in the pair is is selling above the overall median ratio of $netsales_t/holdings_{t-1}$.
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 insurance group (excluding separate accounts) does not meet the $50 billion in assets SIFI designation threshold in any year during our sample period.
NonConc_Pair	An indicator variable equal to 1 if Conc=0 (either Conc_AC or Conc_I) for both insurers in a pair, 0 otherwise.
P&C	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 P&C=1 for both insurers in a pair, 0 otherwise.
PSIFI	An indicator variable equal to 1 if an insurance company (excluding separate accounts) could potentially be designated as a SIFI because it meets the $50 billion in assets threshold in at least one year during our sample period.
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_Pair_High	An indicator variable equal to 1 if RBC is above the first quartile RBC ratio for the sample in a given year for both insurers in a pair, 0 otherwise.
RBC_Pair_Low	An indicator variable equal to 1 if RBC is at or below the first quartile RBC ratio in a given year for both insurers in a pair, 0 otherwise.
RetCorr_Pair	For a pair of insurers, the annual correlation of daily holding-period returns calculated at year end for each pair of insurers.
Similarity	Similarity measure based on the cosine similarity between a pair of insurers' asset class portfolio weights (Similarity_ AC) or between a pair of insurers' issuer portfolio weights (Similarity_I).
Small	Small is an indicator variable equal to 1 if a non-PSIFI insurer's portfolio assets are below the sample median at calendar year end, 0 otherwise.
Small_Pair	An indicator variable equal to 1 if Small=1 for both insurers in a pair, 0 otherwise.

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 include 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, Knowles, and Kell, 2005), on the most utilized unsupervised clustering algorithms (Self Organizing Maps, Self Organizing Tree Maps, K-means, hierarchical).

The optimal number of clusters (N_{opt}) is finally obtained computing the mode of the optimal number of clusters in each of the 12 years (N_t).

$$N_{opt} = Mo(N_t) \tag{4}$$

Coherently, the optimal algorithm (C_{opt}) is derived by counting the number of times an algorithm appears as locally optimal over the 12 years (C_t) and selecting the maximum value.

$$C_{opt} = Max(\sum_{i=1}^{12} C_t) \tag{5}$$

We run the unsupervised *K-means* algorithm (MacQueen, 1967), yearly, with the following setting:[21]

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

ii) for the following year (Y_t with $t = [2 : 12]$) the centroids obtained by 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 of the other years is set to introduce a *short-time*

[21] The algorithm is based a finite number of cycle 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.

memory effect in the evolution of the clusters over time. The link of the cluster structures over time allows us to observe the transitions of the insurers among clusters year by year.

We then analyze the clusters looking at:

i) size both in term of number of companies and volumes (amount of assets);

ii) centroids' structure;

iii) transitions of companies among clusters over time.

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

$$\overline{x^i} = \frac{1}{12}\sum_{t=1}^{12}(x^i_t) \tag{6}$$

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

$$Flow_{i,t} = \sum_{j \neq i} I_{j,t} In - \sum_{j=i} I_{j,t} Out \tag{7}$$

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 *kmeans*. A clear indication emerges for the optimal number of clusters being 3 clusters as this appears 21 times over 33 possible outcomes. [22]

Cluster Validation

To validate the cluster approach we selected 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*.

Connectivity (Handl, Knowles, and Kell, 2005) Connectivity measures 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 the number of attributes of each observation (namely the coordinate of the observation in an M-dimensional space) and $nn_{i(j)}$ the j^{th} nearest

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

neighbor of observation i. Let $x_{i,nn_{i(j)}}$ be

$$x_{i,nn_{i(j)}} = \begin{cases} 0, & \text{if } i \text{ and } i \text{ are in the same cluster} \\ \dfrac{1}{j}, & otherwise \\ \\ \end{cases} \tag{8}$$

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

$$Conn(\mathcal{C}) = \sum_{i=1}^{N} \sum_{j=1}^{L} x_{i,nn_{i(j)}} \tag{9}$$

where L defines the number of neighbor to use.

The *connectivity* has values between 0 and ∞ and should be minimized.

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

$$S(i) = \frac{b_i - a_i}{max(b_i, a_i)}, \tag{10}$$

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:

$$b_i = \min_{C_k \in \mathcal{C} \ C(i)} \sum_{j \in C_k} \frac{dist(i,j)}{n(C_k)}, \tag{11}$$

where $C(i)$ is the cluster containing observation i, $dist(i,j)$ is the distance between observation i and j and $n(C)$ is the cardinality of cluster C.

Silhouette Width values lies in $[-1, 1]$ and it should be maximized.

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

$$D(\mathcal{C}) = \frac{\min_{C_k, C_l \in \mathcal{C}, C(k) \neq C_l} (\min_{i \in C_k, j \in C_j} dist(i,j))}{\max_{C_m \in \mathcal{C}} diam(C_m)}, \tag{12}$$

where $diam(C_m)$ is the maximum distance between observations in cluster C_m.

Dunn Index lies between $[0, \infty]$ and should be maximized.

Figure 1: Portfolio Composition Through Time

This figure presents the cross-sectional average composition of insurer portfolios over 2002-2014 by broad asset class.

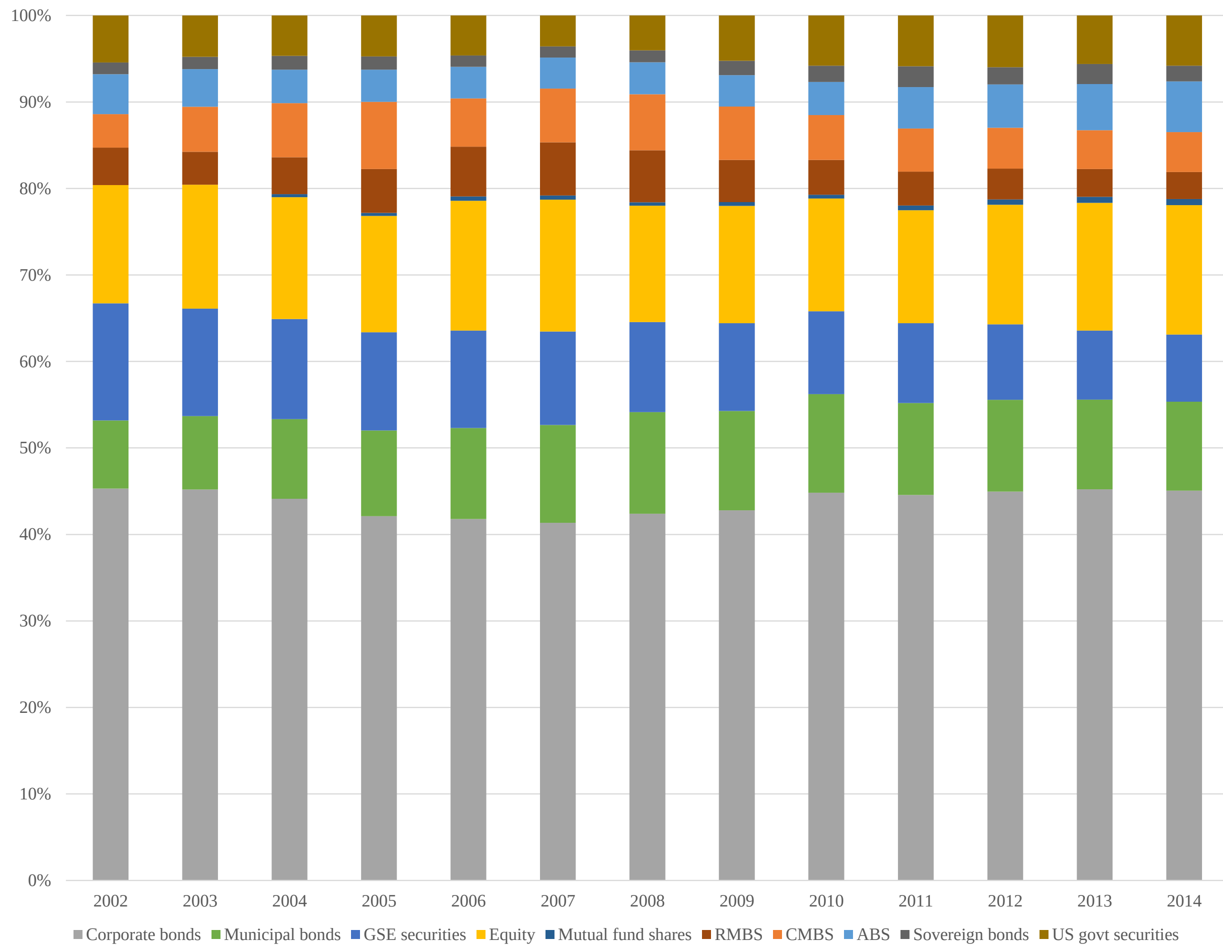


Figure 2: Cluster Structure for Holdings by Broad Asset Classes

This figure presents the average broad asset class dollar composition for three clusters based on the holdings of all insurers over 2002-2014.

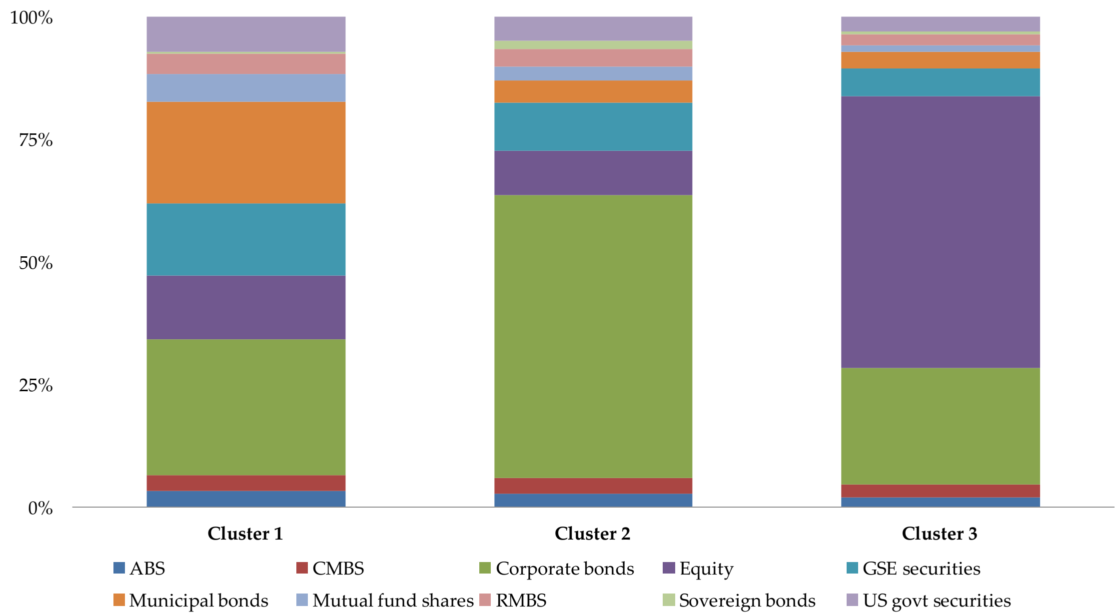
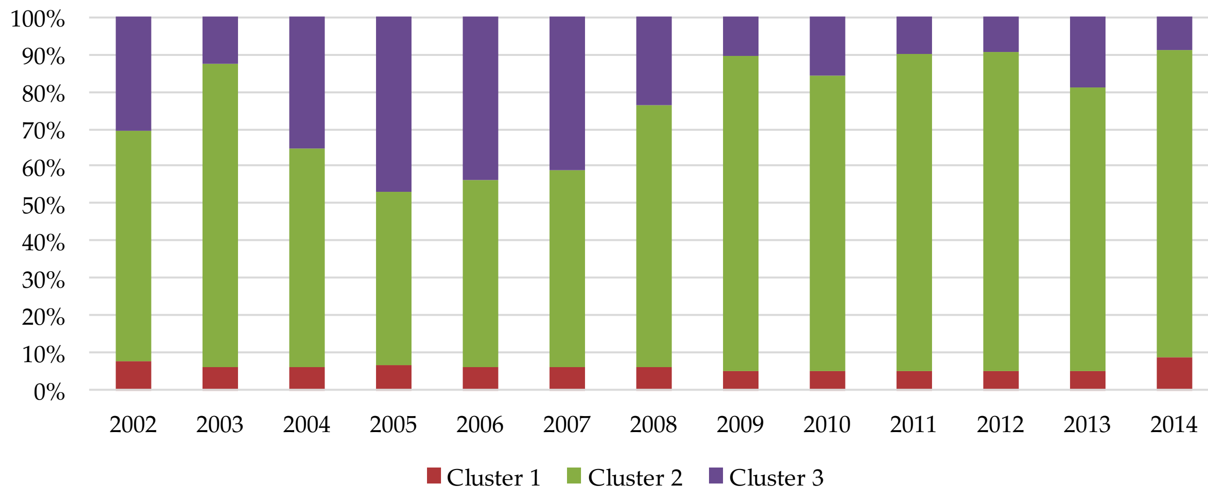
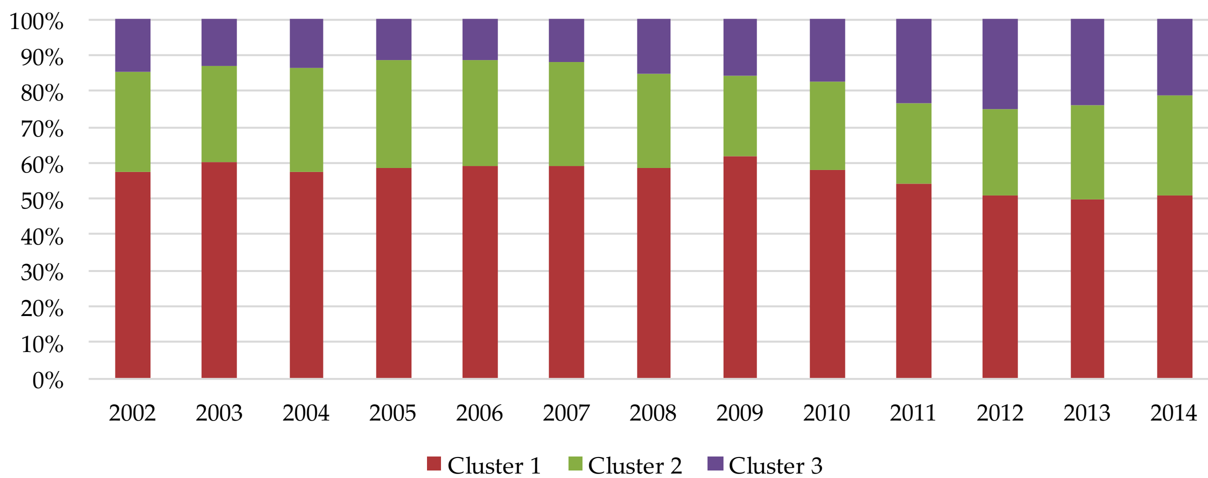


Figure 3: Cluster Distribution of Broad Asset Classes for PSIFIs and Non-PSIFIs

The figure depicts the distribution of PSIFI and non-PSIFI insurers among the three clusters from 2002 to 2014. PSIFI insurer is defined as any insurer with total assets (excluding separate accounts) of at least $50 billion in any year of the sample period.



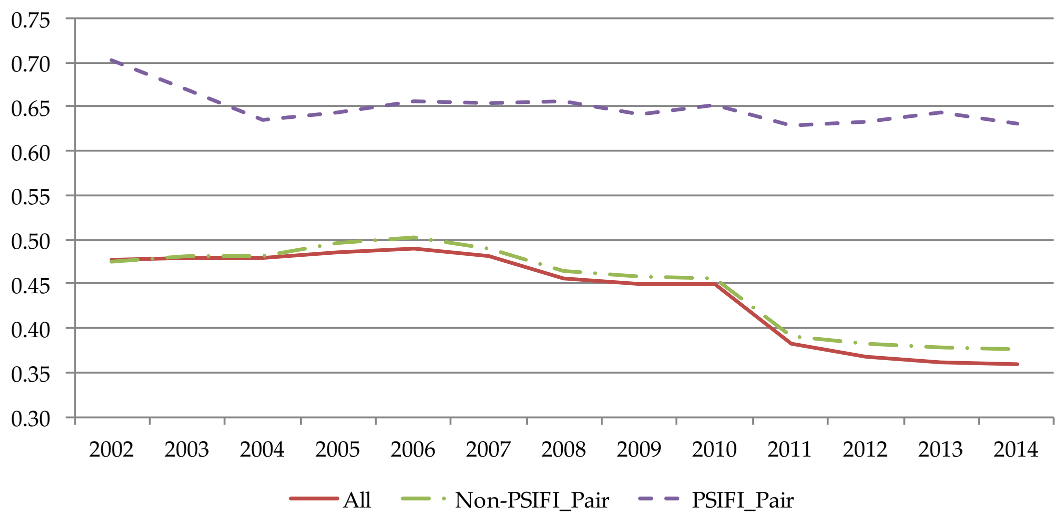
(a) PSIFI



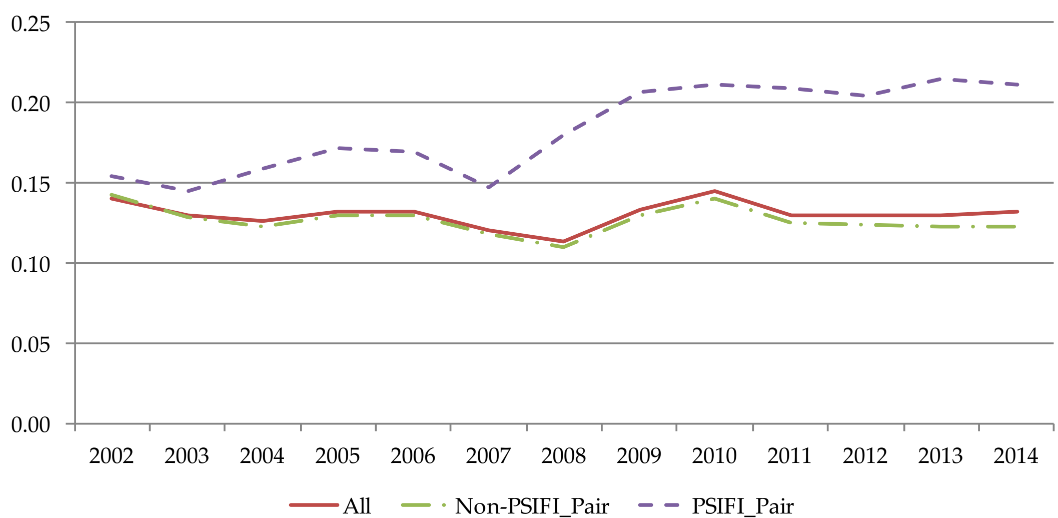
(b) Non-PSIFI

Figure 4: Pairwise Portfolio Similarity

The figure shows average pairwise portfolio similarity computed at the (a) asset class and (b) issuer level over 2002-2014. The red line represents the average for the sample of all insurers. The violet line represents the average for PSIFI insurers. The green line represents the average for non-PSIFI insurers.



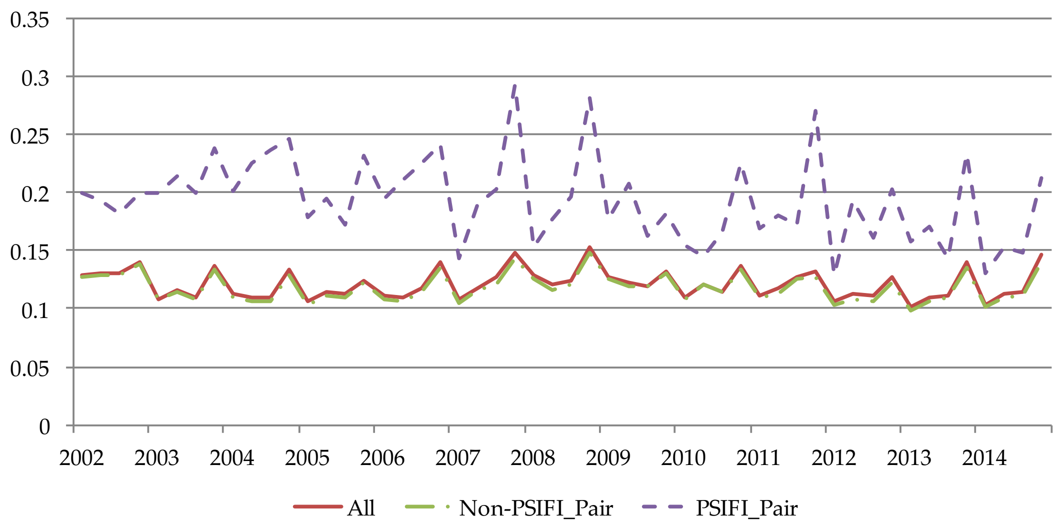
(a) Asset Class Similarity



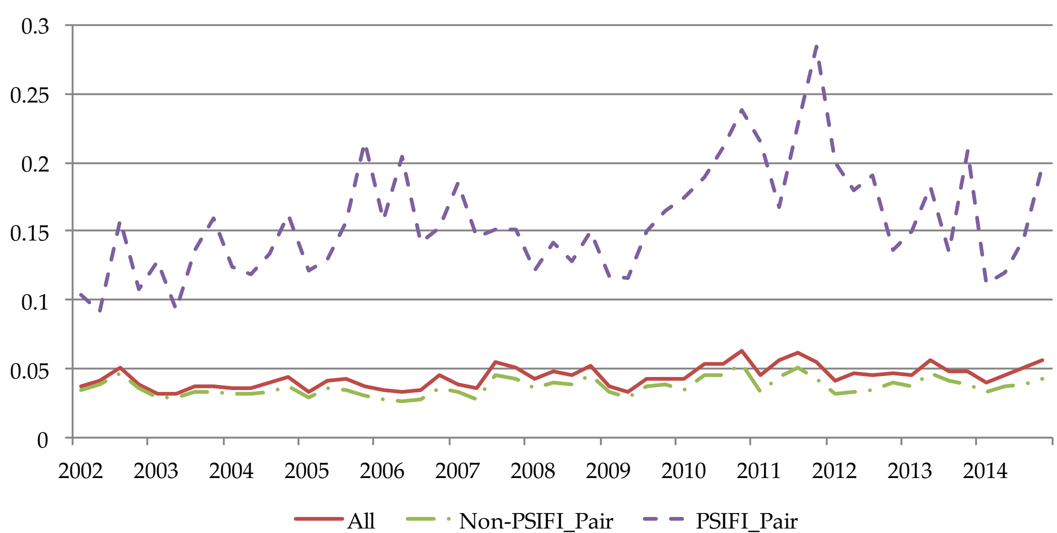
(b) Issuer Similarity

Figure 5: Quarterly Pairwise Sales Similarity

The figure shows average quarterly pairwise sales similarity computed at the (a) asset class and (b) issuer level from 2002-2014. The red line represents the average for the sample of all insurers. The violet line represents the average for the subsample of PSIFI insurers. The green line represents the average for the subsample of non-PSIFI insurers.



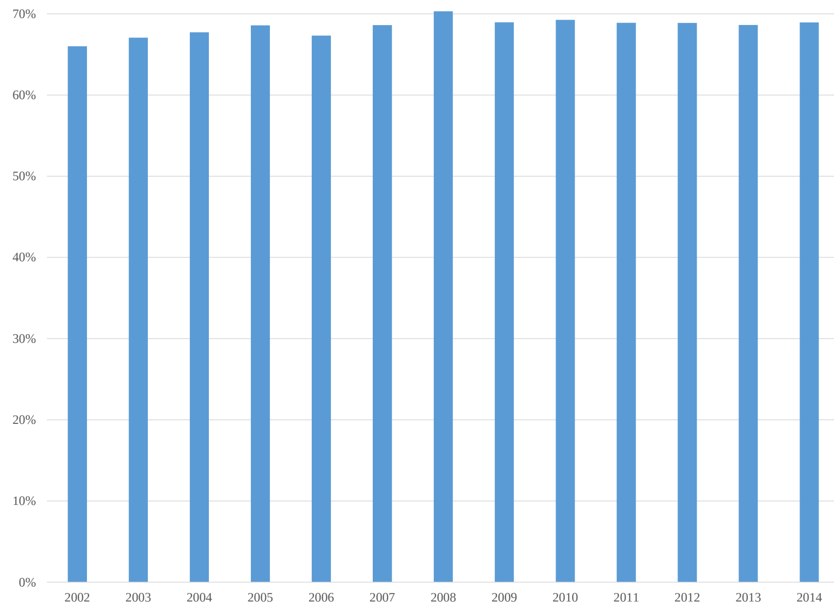
(a) Asset Class Similarity



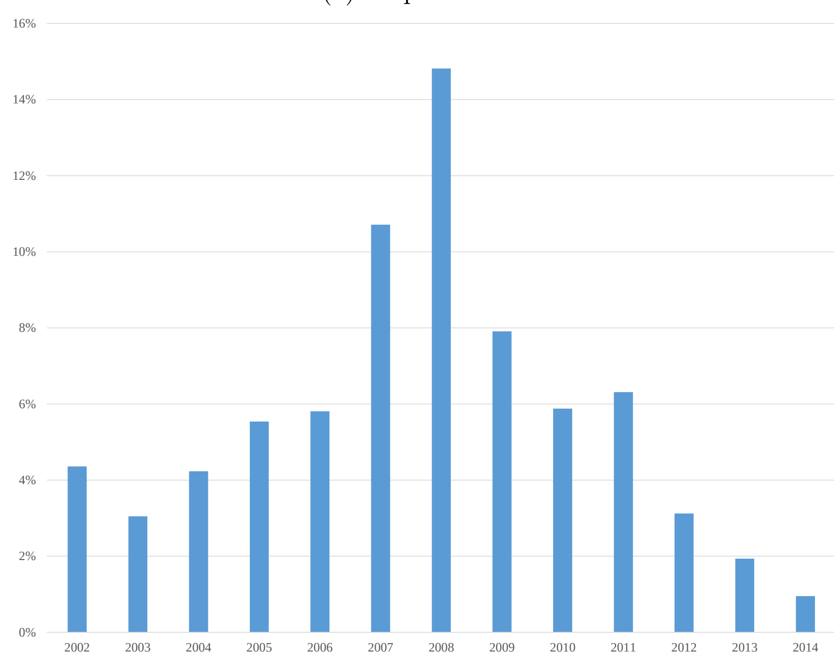
(b) Issuer Similarity

Figure 6: Proportion of Holdings of Illiquid and Downgraded Securities

This figure presents the proportion of holdings (out of 100%) that are composed of (a) illiquid or (b) downgraded issuers respectively for 2002-2014.



(a) Illiquid Issuers



(b) Downgraded Issuers

Table 1: Portfolio Composition and Other Insurer Characteristics

The table presents portfolio composition and other insurer characteristics statistics for the whole sample of insurer groups from 2002 to 2014. P&C insurers operate predominantly in property and casualty lines of business. PSIFI indicates potentially systemically important insurers defined as those with total assets (excluding separate accounts) above $50B in at least one year during the sample period. Corporate bonds, GSE securities, Municipal bonds, US govt securities, RMBS, CMBS, ABS, Sovereign bonds, Equity, and Mutual fund shares are the dollar-value percentages of an insurer's portfolio invested in these broad asset classes. Number of securities is the number of unique 9-digit CUSIPs in an insurer's portfolio in a given year. Number of issuers is the number of unique issuers, identified using 6-digit CUSIPs, in an insurer's portfolio in a given year. Asset class concentration is a Herfindahl index constructed for each insurer in each year as the sum of the squared weights of asset classes in its portfolio. Issuer concentration is a Herfindahl index constructed for each insurer in each year as the sum of the squared weights of issuers in its portfolio. Issuer/asset class weights are calculated as the dollar amount invested in each issuer/asset class relative to the total value of an insurer's portfolio. TA measures total assets at calendar year end. Investment Portfolio Value is the total value of security holdings disclosed on Schedule D at calendar year end. 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
Broad 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 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
US govt 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															
Asset class concentration	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
Issuer concentration	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: Determinants of Portfolio Holdings Similarity

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is the portfolio similarity of a pair of insurers measured at the asset class or issuer level. All independent variables are defined in Appendix B. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	Asset Class Similarity			Issuer Level Similarity		
	All	Non-PSIFI	PSIFI	All	Non-PSIFI	PSIFI
	(1)	(2)	(3)	(4)	(5)	(6)
Life_Pair	0.062***	0.052***	0.192***	0.000	-0.002*	0.027***
	(7.46)	(6.02)	(21.30)	(0.03)	(-1.87)	(3.87)
PC_Pair	0.026***	0.030***	0.068***	0.020***	0.022***	0.022
	(5.30)	(5.85)	(4.86)	(24.93)	(21.71)	(1.69)
PSIFI_Pair	0.135***			0.074***		
	(18.32)			(18.28)		
Non-PSIFI_Pair	0.049***			-0.011*		
	(6.64)			(-2.09)		
Big_Pair		0.075***			0.025***	
		(13.62)			(7.99)	
Small_Pair		-0.029***			-0.021***	
		(-12.74)			(-5.99)	
Conc_Pair_AC	-0.031***	-0.017***	-0.261***			
	(-4.87)	(-3.20)	(-9.13)			
NonConc_Pair_AC	0.138***	0.114***	0.227***			
	(19.68)	(20.21)	(8.42)			
Conc_Pair_I				0.061***	0.071***	-0.044
				(34.13)	(27.28)	(-0.97)
NonConc_Pair_I				-0.006***	-0.017***	0.082***
				(-4.96)	(-7.72)	(3.90)
Constant	0.385***	-0.103***	-0.036***	0.127***	-0.018***	0.067***
	(-130.21)	(-118.17)	(-19.62)	(-223.73)	(-176.62)	(48.96)
Year FE	Y	Y	Y	Y	Y	Y
N	10,605,566	10,077,756	6,608	10,605,566	10,077,756	6,608
R^2	0.092	0.105	0.305	0.028	0.035	0.072

Table 3: Predicting Sales Similarity with Portfolio Similarity

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is insurers' quarterly pairwise net sales similarity at the asset class and issuer level. *Similarity_ AC* is the cosine similarity between a pair of insurers' asset class portfolio weights and *Similarity_I* is the cosine similarity between a pair of insurers' issuer portfolio weights. *High_Sales* is an indicator variable equal to 1 if, during a given quarter, each insurer in the pair is selling above the overall median ratio of $netsales_t/holdings_{t-1}$ for all insurers. All other independent variables are defined in Appendix B and 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.

	Asset class Similarity			Issuer Level Similarity		
	All	Non-PSIFI	PSIFI	All	Non-PSIFI	PSIFI
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC	0.062***	0.058***	0.134***			
	(22.43)	(20.47)	(10.68)			
Similarity_I				0.239***	0.221***	0.633***
				(32.98)	(31.37)	(23.71)
High_Sales	0.007***	0.008***	0.014	0.006***	0.006***	0.052**
	(5.85)	(5.98)	(0.36)	(5.85)	(6.20)	(2.42)
Similarity_AC*High_Sales	0.037***	0.038***	0.032			
	(11.63)	(11.65)	(0.60)			
Similarity_I*High_Sales				0.120***	0.120***	0.312***
				(13.21)	(13.66)	(3.94)
Life_Pair	-0.001	-0.001	-0.004	-0.006***	-0.006***	0.022***
	(-1.13)	(-1.10)	(-0.60)	(-7.71)	(-11.44)	(2.97)
PC_Pair	0.009***	0.011***	-0.002	-0.004***	-0.001*	-0.025***
	(8.47)	(10.21)	(-0.18)	(-8.12)	(-1.99)	(-4.78)
PSIFI_Pair	0.047***			0.082***		
	(12.86)			(20.45)		
Non-PSIFI_Pair	-0.024***			-0.040***		
	(-12.78)			(-29.05)		
Big_Pair		0.013***			0.023***	
		(16.96)			(29.13)	
Small_Pair		-0.004***			-0.016***	
		(-5.50)			(-26.47)	
Conc_Pair_AC	-0.003**	-0.001	-0.001			
	(-2.55)	(-0.59)	(-0.04)			
NonConc_Pair_AC	0.009***	0.007***	0.008			
	(9.47)	(8.01)	(0.77)			
Conc_Pair_I				-0.000	0.008***	0.000
				(-0.36)	(7.76)	(0.01)
NonConc_Pair_I				-0.006***	-0.013***	-0.024**
				(-9.18)	(-19.46)	(-2.41)
Constant	0.090***	0.065***	0.113***	0.039***	-0.005***	0.049***
	(37.04)	(46.94)	(11.66)	(36.84)	(-5.07)	(4.96)
Year-Quarter FE	Y	Y	Y	Y	Y	Y
N	18,431,156	17,125,624	23,440	20,602,406	19,216,681	23,564
R^2	0.015	0.015	0.039	0.114	0.118	0.194

Table 4: Sales Similarity and RBC Ratio

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is insurers' quarterly pairwise net sales similarity at the asset class and issuer level. *Similarity_ AC* is the cosine similarity between a pair of insurers' asset class portfolio weights and *Similarity_I* is the cosine similarity between a pair of insurers' issuer portfolio weights. (*RBC_High_Pair*) is equal to 1 if both insurers are above the first quartile RBC ratio for the sample and (*RBC_Low_Pair*) is equal to 1 if both insurers are at or below the first quartile RBC ratio for the sample. All independent variables are defined in Appendix B and 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.

	Asset Class Similarity			Issuer Level Similarity		
	All	Non-PSIFI	PSIFI	All	Non-PSIFI	PSIFI
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC	0.065***	0.061***	0.135***			
	(23.97)	(22.00)	(10.56)			
Similarity_I				0.278***	0.257***	0.667***
				(39.79)	(37.74)	(23.73)
RBC_High_Pair	0.000	0.000	0.000	0.001***	0.001***	0.008
	(-0.34)	(0.30)	(0.00)	(2.93)	(3.19)	(0.46)
Similarity_AC*RBC_High_Pair	0.006***	0.007***	-0.022			
	(3.29)	(3.60)	(-0.40)			
Similarity_I*RBC_High_Pair				-0.011**	0.000	0.019
				(-2.12)	(-0.09)	(0.15)
RBC_Low_Pair	-0.006***	-0.004***	-0.116**	-0.002***	0.000	-0.100*
	(-4.48)	(-3.17)	(-2.05)	(-2.88)	(0.11)	(-1.89)
Similarity_AC*RBC_Low_Pair	0.012***	0.012***	0.122			
	(4.17)	(4.03)	(0.61)			
Similarity_I*RBC_Low_Pair				0.002	0.009	1.147**
				(0.27)	(1.06)	(2.67)
Life_Pair	-0.003**	-0.003**	-0.004	-0.007***	-0.007***	0.026***
	(-2.17)	(-2.14)	(-0.56)	(-8.70)	(-12.23)	(3.26)
PC_Pair	0.011***	0.012***	0.001	-0.004***	0.000	-0.030***
	(9.55)	(11.18)	(0.06)	(-7.02)	(-0.78)	(-5.50)
PSIFI_Pair	0.046***			0.079***		
	(12.66)			(19.91)		
Non-PSIFI_Pair	-0.021***			-0.039***		
	(-11.62)			(-28.87)		
Big_Pair		0.012***			0.022***	
		(15.43)			(28.76)	
Small_Pair		-0.004***			-0.016***	
		(-6.13)			(-27.02)	
Conc_Pair_AC	-0.004***	-0.002*	-0.003			
	(-3.64)	(-1.79)	(-0.13)			
NonConc_Pair_AC	0.010***	0.009***	0.007			
	(10.08)	(8.95)	(0.65)			
Conc_Pair_I				0.000	0.008***	0.015
				(0.35)	(8.06)	(0.63)
NonConc_Pair_I				-0.007***	-0.013***	-0.036***
				(-10.34)	(-20.14)	(-3.37)
Constant	0.086***	0.061***	0.114***	0.032***	-0.010***	0.053***
	(34.85)	(43.85)	(11.95)	(32.76)	(-10.31)	(5.22)
Quarter FE	Y	Y	Y	Y	Y	Y
N	17167641	15907945	23440	19169518	17833090	23564
R^2	0.012	0.012	0.038	0.108	0.111	0.184

Table 5: Sales Similarity, Liquidity and Downgrades by RBC

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is insurers' quarterly pairwise sales similarity at the sector and issuer level. *Similarity_AC_Liquid* is the portfolio similarity of issuers that fall within the following broad asset classes that are considered liquid: equity, mutual fund shares, US government securities, GSE securities, and sovereign bonds. *Similarity_AC_Illiquid* is the portfolio similarity of issuers that fall within the following broad asset classes that are considered illiquid: corporate bonds, municipal bonds, RMBS, CMBS and ABS. *Similarity_ Downgraded* is the portfolio similarity of issuers that are downgraded in the following year. *Similarity_ NotDowngraded* is the portfolio similarity of issuers that are not downgraded in the following year. (*RBC_High_Pair*) is equal to 1 if both insurers are above the first quartile RBC ratio for the sample and (*RBC_Low_Pair*) is equal to 1 if both insurers are at or below the first quartile RBC ratio for the sample. All independent variables are defined in Appendix B and 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.

	Asset Class Similarity			Issuer Level Similarity		
	All	Non-PSIFI	PSIFI	All	Non-PSIFI	PSIFI
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC_Illiquid	0.044***	0.041***	0.051***			
	(25.25)	(22.72)	(3.38)			
Similarity_AC_Liquid	0.039***	0.036***	0.075***			
	(15.49)	(14.32)	(5.31)			
Similarity_I_Downgraded				0.063***	0.050***	0.196***
				(15.77)	(16.93)	(9.01)
Similarity_I_NotDowngraded				0.287***	0.266***	0.566***
				(36.35)	(34.98)	(17.67)
RBC_High_Pair	-0.000	-0.000	0.001	0.002**	0.001	0.058*
	(-0.18)	(-0.02)	(0.03)	(2.39)	(1.42)	(1.79)
Similarity_AC_Illiquid*RBC_High_Pair	0.005***	0.005***	0.042			
	(3.34)	(3.38)	(0.76)			
Similarity_AC_Liquid*RBC_High_Pair	0.001	0.002	-0.068			
	(0.33)	(0.90)	(-1.11)			
Similarity_I_Downgraded*RBC_High_Pair				0.004	0.010**	-0.190***
				(0.91)	(2.29)	(-3.27)
Similarity_I_NotDowngraded*RBC_High_Pair				-0.012*	-0.001	0.178
				(-1.81)	(-0.15)	(1.49)
RBC_Low_Pair	-0.005***	-0.004**	0.002	-0.002**	-0.001	-0.057
	(-3.20)	(-2.27)	(0.05)	(-2.46)	(-1.38)	(-1.00)
Similarity_AC_Illiquid*RBC_Low_Pair	0.004*	0.004	-0.279			
	(1.69)	(1.60)	(-1.24)			
Similarity_AC_Liquid*RBC_Low_Pair	0.004*	0.004*	0.265			
	(1.74)	(1.90)	(0.82)			
Similarity_I_Downgraded*RBC_Low_Pair				-0.010*	-0.002	-0.296
				(-1.95)	(-0.41)	(-1.26)
Similarity_I_NotDowngraded*RBC_Low_Pair				0.007	0.012	1.412**
				(0.68)	(1.19)	(2.19)
Life_Pair	-0.003***	-0.003**	0.004	-0.008***	-0.009***	0.022***
	(-2.76)	(-2.46)	(0.70)	(-9.61)	(-13.33)	(2.94)
PC_Pair	0.010***	0.012***	0.009	-0.004***	-0.001	-0.020***
	(7.90)	(9.38)	(0.84)	(-6.23)	(-1.04)	(-3.49)
PSIFI_Pair	0.048***			0.064***		
	(12.83)			(16.64)		
Non-PSIFI_Pair	-0.021***			-0.035***		
	(-11.73)			(-28.34)		
Big_Pair		0.013***			0.021***	
		(15.15)			(26.74)	
Small_Pair		-0.006***			-0.015***	
		(-8.95)			(-26.28)	
Conc_Pair_I	0.005***	0.008***	-0.022	0.004***	0.011***	0.020
	(4.11)	(6.93)	(-0.81)	(2.70)	(7.17)	(0.78)
NonConc_Pair_I	0.002**	-0.001	0.029***	-0.011***	-0.015***	-0.064***
	(2.19)	(-1.22)	(2.88)	(-12.76)	(-18.88)	(-6.68)
Constant	0.075***	0.052***	0.086***	0.028***	-0.013***	0.019
	(26.84)	(28.69)	(7.38)	(21.46)	(-10.50)	(1.67)
Quarter FE	Y	Y	Y	Y	Y	Y
N	16,373,088	15,143,491	23,440	13,176,795	12,074,530	23,560
R^2	0.012	0.012	0.039	0.116	0.116	0.206

Table 6: Sales Similarity, Liquidity and Downgrades By Crisis Periods

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is insurers' quarterly pairwise net sales similarity at the asset class and issuer level. *Similarity_AC_Liquid* is the portfolio similarity of securities that fall within the following broad asset classes that are considered liquid: equity, mutual fund shares, US government securities, GSE securities, and sovereign bonds. *Similarity_AC_Illiquid* is the portfolio similarity of securities that fall within the following broad asset classes that are considered illiquid: corporate bonds, municipal bonds, RMBS, CMBS and ABS. *Similarity_ Downgraded* is the portfolio similarity of issuers that are downgraded in the following year. *Similarity_ NotDowngraded* is the portfolio similarity of issuers that are not downgraded in the following year. *Crisis* is a dummy variable equal to 1 for the years 2007 to 2009 and *Post-Crisis* is a dummy variable equal to 1 for the years 2010 to 2014. All independent variables are defined in Appendix B and 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.

	Asset Class Similarity			Issuer Level Similarity		
	All	Non-PSIFI	PSIFI	All	Non-PSIFI	PSIFI
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC_Illiquid	0.039***	0.037***	-0.013			
	(27.72)	(22.06)	(-0.53)			
Similarity_AC_Liquid	0.028***	0.026***	0.101**			
	(16.66)	(13.01)	(3.91)			
Similarity_I_Downgraded				0.060***	0.049***	0.090***
				(30.52)	(20.41)	(18.28)
Similarity_I_NotDowngraded				0.271***	0.248***	0.778***
				(19.96)	(22.32)	(10.37)
Crisis	-0.011*	-0.009*	-0.059**	0.003	0.003	-0.013
	(-3.05)	(-2.57)	(-3.28)	(2.30)	(2.33)	(-1.06)
Similarity_AC_Illiquid*Crisis	0.011	0.011	0.070*			
	(1.93)	(1.88)	(2.45)			
Similarity_AC_Liquid*Crisis	0.019***	0.019***	-0.018			
	(7.61)	(6.81)	(-1.11)			
Similarity_I_Downgraded*Crisis				0.007	0.005	0.142***
				(1.94)	(1.22)	(8.85)
Similarity_I_NotDowngraded*Crisis				0.010	0.018	-0.236*
				(0.59)	(1.09)	(-2.70)
Post-Crisis	-0.014***	-0.011***	-0.086***	0.003**	0.002	-0.039**
	(-24.01)	(-14.74)	(-16.33)	(4.34)	(1.87)	(-5.70)
Similarity_AC_Illiquid*Post-Crisis	0.008**	0.007*	0.135*			
	(3.34)	(2.53)	(2.90)			
Similarity_AC_Liquid*Post-Crisis	0.021***	0.020**	-0.058			
	(7.02)	(5.77)	(-1.33)			
Similarity_I_Downgraded*Post-Crisis				-0.011***	-0.007*	0.260***
				(-6.10)	(-2.95)	(10.49)
Similarity_I_NotDowngraded*Post-Crisis				0.021	0.027	-0.363**
				(1.41)	(1.71)	(-5.70)
Life_Pair	-0.003	-0.003	0.004	-0.008***	-0.009***	0.025**
	(-1.77)	(-1.50)	(0.77)	(-28.14)	(-21.07)	(4.38)
PC_Pair	0.010**	0.011**	0.006	-0.004***	-0.001	-0.023*
	(4.28)	(5.02)	(0.39)	(-21.24)	(-2.31)	(-2.67)
PSIFI_Pair	0.048**			0.066***		
	(5.66)			(13.15)		
Non-PSIFI_Pair	-0.021***			-0.036***		
	(-5.93)			(-18.17)		
Big_Pair		0.012***			0.022***	
		(23.15)			(16.19)	
Small_Pair		-0.005***			-0.015***	
		(-11.26)			(-16.48)	
Conc_Pair_I	0.005**	0.007***	-0.032	0.004**	0.011***	0.020
	(5.40)	(10.12)	(-0.95)	(3.43)	(10.63)	(0.94)
NonConc_Pair_I	0.002*	-0.001	0.031	-0.010***	-0.015***	-0.074***
	(2.85)	(-1.82)	(1.93)	(-23.16)	(-23.22)	(-7.82)
Constant	0.085***	0.062***	0.090**	0.033***	-0.007**	0.036
	(31.85)	(39.51)	(4.73)	(35.36)	(-4.24)	(1.74)
Quarter FE	Y	Y	Y	Y	Y	Y
N	17,435,422	16,166,316	23,440	13,876,460	12,744,887	23,560
R^2	0.011	0.011	0.033	0.112	0.113	0.203

Table 7: Sales Similarity and Return Correlation - CRSP Subsample

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is insurers' net sales similarity at the asset class and issuer levels for quarters Q1 to Q4 in year $t+1$. *Similarity_ AC* is the cosine similarity between a pair of insurers' asset class portfolio weights and *Similarity_I* is the cosine similarity between a pair of insurers' issuer portfolio weights. *RetCorr_pair* is the return correlation of pairs of insurers and is measured in the quarter prior to the sales. All other independent variables are defined in Appendix B and 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.

	Asset Class Similarity				Issuer Level Similarity			
	All	All	Non-PSIFI	PSIFI	All	All	Non-PSIFI	PSIFI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RetCorr_pair	0.005	0.003	-0.015*	0.029	0.020**	0.035***	0.030***	-0.003
	(0.64)	(0.40)	(-1.68)	(1.13)	(2.17)	(3.65)	(3.91)	(-0.11)
Similarity_AC		0.069***	0.078***	0.064**				
		(9.75)	(9.14)	(2.60)				
Similarty_I						0.558***	0.513***	0.634***
						(28.68)	(19.89)	(14.72)
Life_Pair	0.011***	0.002	-0.002	-0.004	0.006	-0.009***	-0.009***	0.049***
	(3.52)	(0.65)	(-0.46)	(-0.26)	(1.66)	(-3.06)	(-4.08)	(3.37)
PC_Pair	0.028***	0.024***	0.023***	-0.127***	-0.021***	-0.001	-0.004	0.025
	(4.52)	(3.83)	(3.42)	(-4.07)	(-4.80)	(-0.15)	(-1.02)	(1.33)
PSIFI_Pair	0.033***	0.029***			0.054***	0.047***		
	(6.34)	(5.70)			(8.36)	(7.77)		
Non-PSIFI_Pair	-0.021***	-0.024***			-0.017***	-0.028***		
	(-8.96)	(-9.31)			(-6.31)	(-12.50)		
Big_Pair			0.011***				0.024***	
			(2.97)				(8.01)	
Small_Pair			-0.012***				-0.025***	
			(-2.99)				(-9.19)	
Conc_Pair_AC	-0.014***	-0.014***	-0.011***	0.009				
	(-4.61)	(-4.68)	(-3.09)	(0.52)				
NonConc_Pair_AC	0.015***	0.006*	0.001	0.034***				
	(5.31)	(1.94)	(0.30)	(3.65)				
Conc_Pair_I					0.001	-0.002	0.006	-0.019***
					(0.51)	(-0.70)	(1.53)	(-3.87)
NonConc_Pair_I					-0.000	-0.026***	-0.030***	-0.021*
					(-0.14)	(-7.22)	(-8.99)	(-1.95)
Constant	0.145***	0.112***	0.090***	0.090***	0.072***	0.014***	-0.008*	-0.006
	(47.86)	(25.52)	(18.33)	(4.12)	(21.86)	(4.10)	(-1.93)	(-0.29)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	65,595	65,595	29,403	6,832	70,139	70,139	31,842	7,096
R-squared	0.022	0.026	0.018	0.057	0.029	0.193	0.208	0.192

Table 8: Dollar Sales Similarities of Individual Insurers - CRSP Subsample

The table presents OLS estimation results for the sample of insurer pairs from 2002 to 2014. The dependent variable is, for insurer i, the log sum of all the pairwise insurer's i dot products of net dollar sales with the other $N-1$ companies for quarters Q1 to Q4 in year $t+1$. *Ln(TotalSales)* is the log size of the net sales of insurance company i, *Ln(Size)* is the log size of the holdings of insurance company i, *Similarity_Avg* is the simple average of insurer's i portfolio similarities with the other $N-1$ companies, *Similarity_Avg_BusLines* is the simple average similarity between the business lines of insurer i and those of the other $N-1$ companies, *Conc* is the concentration of insurer's i holdings. 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.

	Asset Class Level			Issuer Level		
	All	All	All	All	All	All
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(TotalSales_AC)	0.791***		0.419***			
	(35.32)		(13.51)			
Ln(TotalSales_I)				0.974***		0.597***
				(32.30)		(13.40)
Ln(Size)		0.935***	0.560***		1.143***	0.532***
		(45.64)	(17.84)		(41.40)	(11.47)
Similarity_Avg_AC	0.171	1.147***	0.973***			
	(0.43)	(3.39)	(2.88)			
Similarity_Avg_I				8.608***	13.249***	10.474***
				(12.78)	(17.71)	(15.16)
Similarity_Avg_BusLines	-0.078	-1.169***	-0.858***	-0.149	-0.737***	-0.548**
	(-0.34)	(-5.90)	(-4.00)	(-0.68)	(-3.11)	(-2.53)
Conc_AC	-1.878***	-0.409	-0.699*			
	(-4.74)	(-1.11)	(-1.87)			
Conc_I				0.667	5.614***	3.710**
				(0.39)	(3.65)	(2.36)
Constant	25.173***	18.318***	19.194***	18.478***	11.018***	13.701***
	(53.08)	(36.32)	(39.45)	(30.99)	(17.27)	(22.47)
Observations	3,213	3,363	3,213	3,351	3,422	3,351
R-squared	0.547	0.563	0.605	0.608	0.591	0.636