Portfolio Similarity and Asset Liquidation in the Insurance Industry *

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Abstract

We examine whether the concern of academics and regulators about the potential for insurers to sell similar assets due to the overlap in their holdings is justified. We measure this overlap using cosine similarity and find that insurers with more similar portfolios have larger subsequent common sales. When faced with a shock to their assets or liabilities, exposed insurers with greater portfolio similarity have larger common sales that impact prices. Our portfolio similarity measure can be used by regulators to predict the common selling of any institution that reports security or asset class holdings regardless of its public company status, making the measure a useful ex-ante predictor of divestment behavior in times of market stress.

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1 Introduction

Identifying the characteristics of entities that may contribute to financial instability is of interest to both regulators and investors. A growing theoretical and empirical literature examines how interconnectedness through the commonality in asset holdings of banks can affect their selling behavior when faced with a liquidity shock (Allen et al. (2012), Acharya and Thakor (2016), and Silva (2019)). Other non-bank institutions, such as insurance companies, also engage in asset sales in times of stress and like banks are subject to risk-based capital requirements. Moreover, insurance companies are linked to the rest of the financial system through their common investments in certain types of assets (Acharya et al. (2011)). As a result, they do not need to fail to propagate risk throughout the system; it may be sufficient for them to "fire sell" assets to produce a significant negative effect (Kartasheva (2014)). Indeed, empirical research supports the notion that insurers' trading behavior during times of stress may impact prices and potentially have a spillover effect on other market participants (Ellul et al. (2011), Ellul et al. (2015), Merrill et al. (2013), and Manconi et al. (2012)).

Regulators have echoed the concerns of academics in their rationale for the designation of three insurers, Prudential, MetLife, and AIG, as nonbank systemically important financial institutions (SIFIs). In particular, the Financial Stability Oversight Council (FSOC) has emphasized that insurers' common investments have the potential to lead to correlated selling that could spillover into the broader economy.[1] There is, however, no empirical evidence that insurers' overall similarity in portfolio holdings leads to more correlated selling, and that such selling impacts prices.

In this paper, we address this gap in the literature by investigating whether insurers with more similar portfolios sell more of the assets they hold in common. We make use of 2002–2014 security-level data from the National Association of Insurance Commissioners (NAIC) to measure the portfolio similarity between a pair of insurers as the cosine similarity of their holdings. Cosine similarity is easily interpretable since it is bounded between zero and one. Thus, two insurers with identical portfolios will have a cosine similarity equal to one and if their portfolios are completely

[1] In its designation of Prudential Financial, Inc., the Financial Stability Oversight Council (FSOC) notes that "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 damage to the broader economy." The Council has since rescinded AIG's, Prudential's, and GECC's SIFI status because of changes the companies made in response to the designation. MetLife's designation was overturned by the courts citing improper economic analysis.

different, the cosine similarity will equal zero. We calculate each pair's year-end portfolio similarity across both broad asset classes and granular security issuers. We show that a pair's portfolio similarity is related to pairwise insurer characteristics such as joint size, portfolio concentration, and business line similarity.

More importantly, we document that our measure of portfolio similarity can predict the incidence and amount of common sales. Utilizing information on insurer trades, we construct a measure of common sales as the dot product of a pair's quarter-end net sales vectors at both the asset class and security issuer levels. We show that there is a strong positive relation between a pair's portfolio similarity and its quarterly common sales during the following year.

The overlap of insurers' portfolios may be driven by liability matching needs and/or risk-seeking behavior (Becker and Ivashina (2015)). To examine the joint effect of liability structure and investment risk, we decompose each insurer's portfolio into high risk versus low risk assets based on whether the assets are more/less likely to experience a price impact given their liquidity and credit quality. We then calculate a pair's portfolio similarity across high risk and low risk assets separately. To determine the expected and unexpected portions of these similarities, given the overlap in a pair's liabilities, we regress high risk and low risk portfolio similarity on liability similarity. We find that the portfolio similarity across high risk assets that support the pair's overlapping liabilities increases common sales the most. In contrast, the "safe" portfolio similarity - expected and across low risk assets - is negatively related to common sales. Thus, the effect of common holdings on common sales appears to be in large part due to insurers' increased risk-taking within the constraints of asset-liability management, which makes it more challenging for regulators to curb it.

Although the similarity in portfolio holdings predicts common sales, it may not necessarily affect asset prices. To test the relationship between portfolio similarity and price impact, we examine the effects of two shocks to the balance sheets of insurers: the bankruptcy of Lehman, and the landfall of hurricanes Katrina and Rita.

In September 2008, Lehman's bankruptcy marked the start of a period of severe market stress. The banking industry faced significant losses as a result of their mortgage lending and securitization activities. AIG's exposure to credit default swaps lead to its near failure and then bailout by the federal government. During this time, both banks and AIG were faced with the need to liquidate holdings to shore up regulatory capital.[2] Thus, the advent of Lehman's bankruptcy provides us with a potential shock to insurers' assets from outside the insurance industry and allows us to study the link between overlap in holdings and forced common sales that could impact prices. We identify insurers more likely to be exposed to this shock as those with relatively large holdings of bank debt or relatively high portfolio similarity with AIG. We find that for exposed pairs, whether to bank debt or AIG holdings, greater portfolio similarity results in greater common sales in the period around Lehman's bankruptcy. This is especially true when the expected portfolio similarity is across high risk assets.

As a result of hurricanes Katrina and Rita, many P&C insurers with exposure in hurricane-affected states were forced to liquidate assets to cover policyholder losses. Examining the effect of the hurricanes on P&C insurers, we document that during the quarter when the hurricanes take place, portfolio similarity increases common sales more for exposed pairs compared to unexposed pairs. Thus, insurers' portfolio similarity, particularly in high risk assets, is strongly related to common sales in times of stress irrespective of whether the stress originates within or without the insurance industry and/or affects assets or liabilities.

To determine whether exposed insurers' common selling due to these shocks results in a price impact, we examine the change in the value of an exposed pair's joint corporate bond holdings. Specifically, for each pair we construct the weighted average yield spread change of its joint portfolio from the quarter before to the quarter after each shock, either Lehman's bankruptcy or the hurricanes' landfall. We find that around the period of the shock, greater portfolio similarity increases the yield spread of a pair's joint corporate bond portfolio more for exposed compared to unexposed pairs. An examination of the types of assets exposed insurers sell reveals that liquid assets such as equity, mutual funds, and U.S. government bonds are sold disproportionately more. Moreover, insurers with greater portfolio similarity sell a higher proportion of corporate debt than insurers with lower portfolio similarity. We, therefore, conclude that the overlap in insurers' holdings may lead to common sales with the potential to depress asset prices under certain circumstances.

Last, we propose an insurer-level portfolio similarity measure, computed as the average portfolio similarity of an insurer with all other insurers in our sample, to identify specific institutions that

[2]AIG received alternate sources of cash in the form of loans from the Federal Reserve Bank of New York and eventually Maiden Lane II. See McDonald and Paulson (2015).

might contribute more to financial instability through their divestment behavior. We show that this measure can be used to predict the extent to which an individual insurer will sell more in common with all other insurers even after controlling for the insurer's own size. Thus, our measure appears to be a useful tool for regulators monitoring the potential for systemic risk contribution of specific institutions.

In particular, regulators have recently proposed a new framework that shifts the focus of systemic risk designation away from an "entity-based" towards an "activity-based" approach.[3]. This shift recognizes that systemic risk can result from correlated activities among many firms that share the same incentives, which could potentially expose them to a common risk factor.[4] Regulators state that they will pay particular attention to corporate and sovereign debt markets in which insurers are major investors. Therefore, the findings of our paper may help regulators understand, identify, and monitor activities such as common investments in these markets where insurers' divesting behavior may amplify systemic risk.

This paper adds to a growing literature on whether institutional investors' herding in asset allocation and liquidation impacts prices. Prior studies focus only on investment in traded corporate bonds and document that under certain circumstances herding can affect bond prices (Ellul et al. (2011), Chiang and Niehaus (2016), Cai et al. (2019), Nanda et al. (2017), and Chaderina et al. (2018)). For example, Murray and Nikolova (2019) show that because insurers are important players in corporate bond markets, their similar investment preferences cause distortions in the cross-section of corporate bond returns. We provide a new measure of commonality in portfolio holdings that extends to the entirety of insurers' portfolios, instead of being limited to just a particular asset class. This is an important distinction for several reasons. First, publicly traded corporate bonds comprise only a fifth of the assets held by the insurance industry.[5] Second, during times of financial instability, sales of fixed income securities other than corporate bonds (e.g., mortgage-backed securities) can contribute to the transmission of risk across these securities'

[3]FSOC issued the proposed guidance on March 6, 2019. The guidance still allows for FSOC to designate individual companies as nonbank SIFIs but only if a potential risk or threat to financial stability cannot be addressed through an activity-based approach. See `https://home.treasury.gov/system/files/261/Notice-of-Proposed-Interpretive-Guidance.pdf`

[4]Khandani and Lo (2007) finds that during the summer of 2007, a fire sale liquidation by a group of hedge funds with similar portfolios created price pressure on a broader set of long/short and long-only equity funds' portfolios.

[5]According to data from insurers' NAIC filings on Schedule D and from TRACE, in 2014 life and P&C insurers held $1.36 trillion of publicly traded corporate bonds (corporate bonds that trade at least once in 2014). The Federal Reserve's Flow of Funds tables indicate that in 2014 these insurers held $6.3 trillion of debt and equity securities.

common holders (Merrill et al. (2013)). And finally, insurers may strategically trade across asset classes to mitigate the price impact of sales (Ellul et al. (2015)). For all of these reasons, considering all assets in insurers' portfolios when establishing a link between portfolio similarity and common sales is important.

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

Finally, unlike other interconnectedness metrics that rely on market-based equity returns, our measure of portfolio similarity can be calculated for any financial institution that discloses asset class or security issuer holdings either publicly or to a regulator. For example, our methodology can be applied to the portfolio holdings of banks (Cai et al. (2018)), hedge funds (Sias et al. (2016)), and money market funds, to name a few, allowing regulators to monitor the potential for common sale spillovers from a wide variety of market participants. As a testament to its relevance, we find a positive ranked correlation between portfolio similarity and SRISK (Brownlees and Engle (2017)), a measure only available for publicly traded firms. Thus, we conclude that our measure of interconnectedness can be used in tandem with other risk metrics to better monitor financial stability.

2 Data and Summary Statistics

Our sample time period is from 2002 to 2014 and we obtain data on insurers' holdings and trades from their statutory filings with the NAIC as distributed by A.M. Best. For each insurer, Parts 1 and 2 of Schedule D of these filings list the par value and book value of every security held at calendar year-end. We retain all non-negative annual holdings. Parts 3, 4, and 5 of Schedule D list every security an insurer disposed of or purchased during the year along with its par value, disposal/purchase value, and date of disposal/purchase. We exclude any security disposals due to maturity, repayment, calls, or other non-trading activity in order to retain only sales. Since trades are reported as of the date they occur, we aggregate sales and purchases at each quarter-end.

Portfolio holdings, sales, and purchases are reported at the individual security (nine character CUSIP) level. For each insurer, we aggregate this information to either the issuer level or asset class level. To aggregate to the issuer level, we use the first six characters of each CUSIP as the issuer identifier and aggregate all holdings, sales, and purchases of securities that have the same six-character CUSIP.[6] To aggregate to the asset class level, we categorize each security into one of the 34 asset classes listed in Appendix A as follows. First, we classify each security into one of these ten primary asset classes: (1) US government securities, (2) GSE debt and asset-backed securities, (3) municipal bonds, (4) sovereign bonds, (5) corporate bonds, (6) RMBS, (7) CMBS, (8) ABS other than RMBS/CMBS, (9) equity (common and preferred stock), and (10) mutual fund shares. We identify RMBS and CMBS using the NAIC-provided list of PIMCO- and BlackRock-modeled securities.[7] We classify all remaining fixed-income securities using the following sources sequentially: (1) the sector and subsector codes in S&P RatingXpress, then (2) the type and subtype codes in DataScope, then (3) the issue description and issuer name in NAIC Schedule D, and finally (4) the issuer name and collateral asset type in SDC Platinum's New Issues Module. We further refine corporate bonds, municipal bonds, and equity using the issuer's industry or sector information reported in Schedule D. We categorize corporate bonds and equity as undefined if the issuer industry or sector is missing or conflicting.

When aggregating holdings, sales, and purchases to the issuer or asset class level, we use the par value of fixed-income holdings. Since no comparable number exists for equity securities, we aggregate these using their carrying values. We construct quarterly net sales at the issuer level or asset class level as sales minus purchases, whenever sales exceed purchases, and zero otherwise.

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

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

[7] The NAIC changed its capital assessment methodology for certain asset classes by replacing credit ratings as the measure of expected loss with valuation-based loss estimates from PIMCO for RMBS and BlackRock for CMBS. The NAIC publishes the list of PIMCO- and BlackRock-modeled securities annually. For more information on this regulatory change, see Hanley and Nikolova (2020).

our analysis at the group level rather than at the individual insurer level. To do so, we aggregate holdings, net sales, and balance sheet information of the initial sample of 5,369 individual insurers to the group level. This aggregation results in a sample of 2,812 different insurance groups. We refer to these as "insurers" throughout the remainder of the paper.

We also categorize insurers as P&C, life, or other (e.g., health, fraternal, and title) if at least half of an insurer's portfolio assets are held in a given year by companies in the group that are in that line of business. Our sample includes 1,746 P&C and 635 life insurers. Finally, in order to examine whether very large insurers are more likely to have similar portfolios and sell similar assets, we classify insurers as *Large* if they have more than $50 billion in total assets, excluding assets held in separate accounts, in at least one year of the sample period.[8] Based on this size threshold, we classify 38 insurers as large.

Table 1 presents descriptive statistics for the portfolio composition of our sample insurers with detailed variable definitions provided in Appendix B. For each insurer, we compute the time-series average of each variable across the sample period and then report the cross-sectional mean, median, and standard deviation. The average total assets of sample insurers, excluding assets held in separate accounts, are $2.41 billion. Life insurers ($7.54 billion) are much larger than P&C insurers ($0.85 billion). By construction, large insurers have significantly more assets ($99.8 billion) compared to other insurers. The average insurer's investment portfolio is $1.65 billion compared to large insurers which have an average portfolio size of almost $37 billion. As with total assets, life insurers have larger investment portfolios than P&C insurers.

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

The average insurer's portfolio is relatively well balanced among corporate bonds, GSE debt,

[8]The $50 billion size threshold has been previously used by regulators to identify potential candidates for SIFI designation. Our results are robust to using total assets, including those held in separate accounts, as the basis for the classification.

municipal bonds, US government securities, and equity. We also find that portfolio composition differs by line of business and size. Life insurers tend to invest a greater proportion of their portfolio in corporate bonds while P&C insurers hold relatively more municipal bonds and mutual fund shares. Large insurers tend to invest primarily in corporate bonds (53%) and to hold more RMBS, CMBS, and ABS.

Figure 1 summarizes the time-series variation in the insurance industry's aggregate holdings and indicates only small shifts in and out of asset classes through time. Over our sample period, the proportion of insurer portfolios allocated to US government securities increases slightly. The figure also shows that insurers' holdings of RMBS and CMBS increase in the period leading up to the 2007-2009 financial crisis and then gradually decrease consistent with the evidence presented in Hanley and Nikolova (2020). Thus, while aggregate insurer portfolios are relatively stable they do exhibit changes over time, particularly during times of market stress.

In examining the composition of insurer holdings, we find that the average insurer in our sample holds 380 different securities issued by 250 issuers. The median number of securities or issuers held is less than half of the sample average, implying that some insurers invest in significantly more securities and issuers than others. Indeed, life insurers invest in more securities and issuers than do P&C insurers, and large insurers hold an order of magnitude greater number of securities (3,704) and issuers (1,888) than the average insurer.

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

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

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

We next use cluster analysis to examine whether insurers differ in their portfolio allocation strategies and whether their strategies change over time. Cluster analysis allows us to separate insurers into subgroups (clusters), whereby insurers within a cluster have more similar portfolios compared to those outside the cluster. We use a standard cluster analysis approach, which we describe in detail in Appendix C. We find that our sample consists of three distinct clusters suggesting that insurers employ only a small number of portfolio strategies. This differentiates them from mutual funds, which follow a variety of investment strategies.[9]

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

Finally, there is a clear distinction between the portfolio allocation strategies of large insurers and all other insurers as shown in Figure 3. Large insurers' portfolios tend to resemble Cluster 2, which is dominated by corporate bonds. All other insurers' portfolios are similar to Cluster 1, which is diversified across different primary asset classes.

3 Measures of Portfolio Similarity and Common Sales

In order to test whether insurers with more similar portfolios are more likely to sell in a related fashion and affect asset prices, we need measures of the overlap in insurer portfolios and overlap in insurer sales. In this section, we describe how we construct these measures.

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

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

3.1 Portfolio Similarity

We measure the portfolio overlap between two insurers using cosine similarity either at the asset class or issuer level. We begin by creating a vector of asset class or issuer portfolio weights using the proportional dollar value of each asset class or issuer of securities held in an insurer's portfolio at calendar year-end. For example, the maximum number of unique asset classes in a given year is 34 and, therefore, each insurer's vector of asset class portfolio weights has a length of 34. If an insurer does not invest in a particular asset class in a given year, its portfolio weight for that asset class is set to zero.[11]

We then calculate the cosine similarity between the portfolios of insurers i and j at year-end t as the dot product of the pair's portfolio weight vectors normalized by the vectors' lengths. That is,

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

where $\boldsymbol{w_{it}}$ and $\boldsymbol{w_{jt}}$ are insurer i and j's vectors of weights at year-end t, respectively. We refer to this variable as portfolio similarity at the asset class (*Similarity_AC*) or issuer (*Similarity_I*) level.

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

Table 2 provides summary statistics for our portfolio similarity measures for the whole sample of insurer pairs as well as for only large pairs. Average asset class similarity, *Similarity_AC*, is 0.45 for the whole sample. Average similarity at the issuer level, *Similarity_I*, is lower (0.12) than at the asset class level because in our sample there are many more issuers (about 32,000) than asset classes (34). The table also shows that large insurers invest in more similar asset classes and issuers than the average insurer.

Figure 4 depicts the time series of the average portfolio similarity at the asset class and issuer level for the sample of all pairs as well as for the subsamples of large pairs and all other pairs

[11] Cosine similarity has been used in text analytics (Hanley and Hoberg, 2010; Hanley and Hoberg, 2012) and hedge fund portfolio analysis (Sias, Turtle, and Zykaj, 2016).

excluding large insurers. The average portfolio similarity at the asset class level has declined over the sample period but has remained relatively constant at the issuer level. Since pairs excluding large insurers make up the majority of our sample, their average portfolio similarity closely mimics that of the full sample of insurers at both the asset class and issuer level. Large insurer pairs have greater asset class and issuer similarity than all other insurers. At the asset class level large pairs' similarity does not fluctuate much over time, but at the issuer level it has increased and the divergence in portfolio similarity between them and other pairs has widened after the 2007-2009 financial crisis.

3.2 Common Sales

We measure the overlap in the selling behavior of a pair of insurers as follows. For each insurer, we first create a vector of quarterly net sales at the asset class or issuer level. We then calculate the common sales of a pair of insurers i and j as the dot product of their quarterly net sales vectors. That is,

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

where $\mathbf{Net\ Sales}_{it}$ and $\mathbf{Net\ Sales}_{jt}$ are insurer i and j's vectors of net sales in quarter t, respectively. Depending on whether we use asset class or issuer net sales, we refer to this quantity as common sales at the asset class ($Common\ Sales\_AC$) or issuer ($Common\ Sales\_I$) level. To account for the high skewness of $Common\ Sales$, in the analyses that follow we use its logarithmic transformation, $Ln(1 + Common\ Sales)$.

It is important to note that our measure of common sales is based on dollar amounts that are not normalized by total holdings or sales. This allows us to focus on large common sales that are most likely to generate a price impact. Because we are interested in the determinants of common sales, for each pair in each quarter we only calculate common sales if both insurers sell at least one asset during the quarter.

Figure 5 presents the quarterly time-series average of $Ln(1+Common\ Sales)$ at the asset class and issuer level for the sample of all pairs as well as for the subsamples of large pairs and all other pairs excluding large insurers. The figure shows that most common sales occur in the last quarter of the year, so in our multivariate analyses we use year-quarter fixed effects to control for this pattern. As with portfolio similarity, large insurer pairs have greater common sales than all other insurers.

Table 2 provides additional summary statistics for common sales. In the sample of all pairs the average of $Ln(1 + Common\ Sales\_AC)$ is almost 15 and that of $Ln(1 + Common\ Sales\_I)$ is six. Large insurer pairs tend to sell more in common both at the asset class and issuer level (34.42 and 31.89, respectively) compared to other insurers. This larger magnitude is not surprising, since large pairs have bigger portfolios and our measure of common sales is not normalized.

4 Determinants of Portfolio Similarity

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

Table 3 presents the results from estimating ordinary least squares (OLS) regressions, in which the dependent variable is portfolio similarity at the asset class level in columns (1) and (2), or issuer level in columns (3) and (4). We find that *Similarity_AC* is greater if the insurers in a pair are both life or P&C, regardless of whether the sample consists of all pairs or only large pairs. This finding is intuitive because insurers likely make asset allocation decisions with their liabilities in mind. Since insurers in the same line of business have similar liabilities, we would expect them to have similar assets as well.[12]

Analyzing portfolio similarity at the issuer level in column (3), we find somewhat different results from those at the asset class level. For the sample of all insurers, a P&C pair has more similar holdings but a life pair does not. When we examine large pairs separately in column (4), we find that their portfolio similarity is greater when they are both in the same line of business,

[12]We explore the effect of liability similarity on portfolio similarity later in the paper.

whether life or P&C.

Portfolio similarity at the asset class or issuer level is greater, the greater the joint size of the pair. This may be due to the fact that as portfolios get larger, pursuing a unique investment strategy becomes more difficult. Alternatively, size may be related to certain aspects of insurers' operations that influence their investment decisions. For example, compared to smaller insurers, larger insurers may underwrite a greater variety of insurance lines that because of asset-liability management may result in a greater variety of investments.

We do not find consistent results for the relation between a pair's portfolio similarity and portfolio concentration. When measured at the asset class level, concentration tends to be negatively related to portfolio similarity. At the issuer level, this relation reverses in the sample of all pairs though not in the subsample of large pairs.

5 Portfolio Similarity and Common Sales

In this section we investigate whether insurers with more similar portfolios have larger subsequent common sales. We then examine whether insurers' asset-liability matching and risk seeking drive the relation between portfolio similarity and common sales.

5.1 Overall Portfolio Similarity

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

To determine whether there is a link between similar holdings and similar sales, we use portfolio similarity to explain both (i) the probability and (ii) the magnitude of common sales. For the probability of common sales, we estimate a probit model in which the dependent variable is an indicator that equals one if $Common\ Sales\_AC$ or $Common\ Sales\_I$ is positive, and zero otherwise.

For the magnitude of common sales, we estimate a tobit model because the dependent variable equals zero for pairs which have no overlap in sales.

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

The relation between portfolio similarity and common sales is economically meaningful as well. In the sample of all pairs, a one percent increase in portfolio similarity at the asset class level leads to an average of 4.55% increase in common sales. In the subsample of large pairs, the same one percent increase in asset class portfolio similarity results in a 4.64% increase in common sales, on average. A one percent increase in portfolio similarity at the issuer level increases common sales by 34.05% for all pairs and 17.62% for large pairs.

We find that common sales are related to a pair's business line similarity, joint size, and joint portfolio concentration, holding portfolio similarity constant. For example, if both insurers in a pair are P&C insurers, the pair has greater common sales at both the asset class and issuer levels. We show that a pair's common sales are positively related to the pair's joint size and although not shown, this finding is robust to excluding large pairs. Thus, while our analysis supports the use of firm size as one criteria for identifying insurers who may affect financial stability through common sales, they also suggest that the $50 billion size threshold used by FSOC is not particularly meaningful.

We also find that the joint portfolio concentration of a pair leads to a decrease in both the probability and magnitude of common sales. The negative coefficient on *Prod_Conc*, whether at the asset class or issuer level, is negative and significant across all columns potentially rebutting the suggestion that it could be a useful metric for identifying SIFIs (Haldane and May (2011), Gai et al. (2011), and Allen et al. (2012)). Instead, our findings support the concerns of Castiglionesi and Navarro (2008), Wagner (2010), Wagner (2011), Ibragimov et al. (2011), and Cont and Wagalath (2016) who argue that although portfolio diversification reduces each institution's individual probability of failure, it can make the potential for common selling higher.

5.2 Effect of Liability Matching and Asset Risk on Common Sales

The portfolio allocation decisions of insurers are based on a variety of factors but liability matching is one of the most important objectives.[13] Thus, it is possible that liability matching explains much of insurers' portfolio choices and therefore, the similarity in insurers' liabilities is responsible for the portfolio overlap we document. In addition, empirical studies show that considerations other than liability matching, in particular capital regulations and the risk seeking behavior they promote, may impact insurers' investment decisions as well (e.g., Becker and Ivashina, 2015, Ellul et al., 2018, Hanley and Nikolova, 2020, and Murray and Nikolova, 2019). In this section, we examine whether these considerations may be driving the relationship between portfolio similarity and common sales.

We begin by splitting an insurer's portfolio into high-risk versus low-risk assets based on whether the assets are more/less likely to experience a price impact when sold. We categorize as high risk all private securities and all RMBS, CMBS, and ABS other than RMBS/CMBS. We define as low risk all publicly issued equity, mutual fund shares, and US government securities. Finally, we classify publicly issued corporate bonds, municipal bonds, GSE securities, and sovereign bonds as low risk if they have an NAIC designation of one and as high risk otherwise. For each insurer pair, we calculate the portfolio similarity separately for the portion of the portfolio that consists of high risk assets and the portion that consists of low risk assets (*Similarity_AC_HighRisk* or *Similarity_AC_LowRisk*).[14]

For each of the two portfolio similarity measures, we determine the portion that can and cannot be explained by the similar liability structure of the insurers in the pair. To do so, for each insurer we use NAIC data on premiums earned by line of business to proxy for liability structure. In the raw data, we observe 11 granular business line categories for life insurers and 34 for P&C

[13] According to the NAIC, "Portfolio compositions vary depending on type of insurer, due mostly to appropriately matching assets to liabilities and taking into consideration relative duration and liquidity risk." See `https://www.naic.org/capital_markets_archive/150622.htm`.

[14] We exclude any insurer whose portfolio does not include at an investment in at least one low risk and one high risk asset (11% of the sample of insurers-years) from these analyses in order to focus on the relative contribution of low and high risk asset similarity in common sales. Including such insurers overweights the contribution of portfolio similarity of low risk assets on common sales. This makes it difficult to discriminate between insurer pairs that both have investment in high risk assets but no overlap from insurer pairs that include insurers with no high risk assets because the cosine similarity is zero in both cases. Since policy makers are interested in whether insurers' overinvestment in high risk assets contributes financial instability, the conclusions are clearer if we include only pairs of insurers that hold both low risk and high assets.

insurers, which we aggregate to 11 broad business line categories. For life insurers these include: (1) industrial life, (2) life insurance, (3) annuities, (4) credit lines, (5) accident and health, and (6) other. For P&C insurers, they include: (7) multiple peril (short tail), (8) financial guarantee, (9) medical professional liability (long tail), (10) reinsurance, and (11) other. For every insurer, we create a vector of weights for each of the 11 categories and then calculate a pair's liability similarity as the cosine similarity between the pair's weight vectors.[15] As with portfolio similarity, the closer liability similarity is to one, the more alike the pair is in terms of liability structure.[16]

We use a pair's liability similarity to decompose *Similarity_AC_HighRisk* and *Similarity_AC_LowRisk* into expected and unexpected components. Specifically, we estimate an OLS regression with either *Similarity_AC_HighRisk* or *Similarity_AC_LowRisk* as the dependent variable and the pair's liability similarity as the main independent variable. The regressions also includes the pairwise indicator variables *Life_Pair* and *PC_Pair* as well as year fixed effects. The expected and unexpected components of the two portfolio similarity measures are the fitted and residual values from these regressions. This process results in four different portfolio similarities, *Similarity_AC_LowRisk_Exp*, *Similarity_AC_LowRisk_Unexp*, *Similarity_AC_HighRisk_Exp*, and *Similarity_AC_HighRisk_Unexp*. For ease of comparison, we standardize all of these portfolio similarities to have a zero mean and unit variance.

We regress common sales on the four portfolio similarity measures and report the results in Table 5. We find that the low risk portfolio similarity that is expected based on the liability similarity of the pair is negatively related to common sales. Therefore, common low risk holdings stemming from similar liabilities have a counter effect on common sales. In contrast, the coefficient on *Similarity_AC_HighRisk_Exp* is positive and by far the largest of all the portfolio similarity coefficients. Thus, investment in similar high risk assets that is related to asset-liability management has strong explanatory power for common sales. Our results indicate that Ellul et al. (2018)'s finding that variable rate annuity providers' increased risk-taking contributes to common selling, applies more broadly to the insurance industry. We also find that unexpected portfolio similarity of

[15]For large pairs, expected and unexpected portfolio similarity across high-risk and low-risk assets is estimated using only large pair observations.

[16]As a reminder, in the main analysis in the paper, we classify insurers' main business line based upon the classification of the majority of their affiliated insurance companies. However, many insurers have both P&C and life companies in their group portfolio. Our measure of liability similarity takes into account the exposure of both insurers to all forms of business lines not just their primary designation.

high risk assets carries a positive and significant coefficient, consistent with concerns that insurers' actions to increase return may contribute to common sales. Collectively, both unexpected asset overlap as well as common investments in high risk assets are significant predictors of insurers' selling behavior. Our findings indicate that insurers' investment decisions related to asset-liability management and asset risk have important implications for common sales.

6 Shocks, Common Sales, and Price Impact

In this section, we investigate whether insurers with more similar portfolios have larger forced common sales that could impact prices by examining the effects of two shocks to insurers' balance sheets. The first is a shock to insurers' assets through their exposure to the banking industry around the bankruptcy of Lehman on September 15, 2008. The second is a shock to P&C insurers' liabilities after hurricanes Katrina and Rita, which made landfall in Florida on August 25, 2005, and Louisiana on September 24, 2005, respectively. These shocks provide us with settings in which common sales may be triggered by events that emanate from outside and inside the insurance industry, respectively.

6.1 Lehman's Bankruptcy

Lehman's bankruptcy filing, the largest in US history, was one of several events to impact financial markets in late 2008. It lead to increased concerns about the creditworthiness of financial institutions in general and banks in particular. The subsequent reduction in bank capital lead to the liquidation of assets, which impacted other financial institutions, and eventually lead to intervention by the federal government. We conjecture that insurers who have higher exposure to the banking sector at the time of the market disruption stemming from Lehman's bankruptcy will be more affected by the devaluation of assets. Therefore, we hypothesize that more exposed insurers should have greater common sales and subsequent increases in portfolio bond yields.

Ideally, to measure an insurer pair's exposure to the banking industry, we would have preferred to calculate the cosine similarity between the holdings of each insurer in the pair with those of banks. Unfortunately, such granular holdings data is not available for banks. Instead, we proxy for insurer pairs' exposure to the banking sector in two ways. First, we assess the exposure of a pair by whether both insurers in the pair hold a large amount of bank debt. We define *Exposed (bank)* as an indicator variable equal to one if the dollar value of bank bonds relative to the dollar value of all corporate bonds held by both insurers in the pair is in the top quartile of the sample for the year, and zero otherwise.

Around the same time as the Lehman failure, AIG's exposure to risks related to securities lending and credit default swaps was the catalyst for a downgrade in its credit rating, creating a collateral shortfall that eventually lead to AIG's near collapse and bail out by the federal government. Arguably, the experience of AIG was the result of its activities supporting the banking sector's mortgage securitization. Therefore, our second indicator of a pair's exposure to the banking industry is the similarity of the pair's portfolios with that of AIG. We define *Exposed (AIG)* as an indicator variable equal to one if both insurers' portfolio similarity with AIG at the issuer level is above the median level in that year, and zero otherwise.[17]

In this section, we focus on the similarity at the issuer level because we use this information in the next section to understand the price impact on insurers' bond holdings as well as on forced sales. To capture the period around Lehman's bankruptcy, which took place towards the end of the third quarter of 2008, we define an indicator variable, *Lehman*, equal to one in 2008Q3 and 2008Q4, and zero otherwise. Panel A of Table 6 presents the results of a tobit estimation of the effect on common sales of a pair's exposure to the banking industry. In columns (1) and (2), where exposure is based on insurers' holdings of bank debt, the coefficient of $Similarity\_I \times Lehman \times Exposed$ is positive and statistically significant in the sample of all pairs. This indicates that for exposed pairs, greater portfolio similarity increases common selling further during the two quarters surrounding the Lehman bankruptcy. When we restrict the sample to only those pairs where both insurers have relatively large holdings of bank debt, the coefficient on the interaction term $Similarity\_I \times Lehman$ is positive and weakly significant.

We find similar results when the definition of *Exposed* is based on a pair's portfolio overlap with AIG's in columns (3) and (4). For pairs that have holdings similar to those of AIG, portfolio similarity further increases common sales in late 2008 and this increase is larger than for unexposed pairs. Even among exposed insurers, the relation between portfolio similarity and common sales

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

is stronger around the period of Lehman's bankruptcy than during other quarters. The economic significance of our findings is also meaningful. For instance, in column (3), a one percent increase in a pair's portfolio similarity leads to an additional 11.54% increase in common sales on average around the period of Lehman's bankruptcy when the pair is exposed rather than unexposed.

The effect of portfolio similarity on common sales is only worrisome if it impacts prices in times of market stress. Specifically, we investigate whether bonds held by pairs with greater portfolio similarity experience a larger drop in value around the time of the Lehman failure. Our approach is similar to that of Manconi et al. (2012) who examine whether the exposure of institutional investors to securitized bonds before the onset of the 2007-2009 financial crisis increases yield spreads more during the crisis. Because of data availability our price impact analysis is limited to corporate bonds.

To match the pairwise nature of our portfolio similarity measure, we construct a pairwise measure of the change in asset prices. Specifically, for each pair of insurers i and j, ΔYS_{ij} is the change in the yield spread of the pair's joint corporate bond portfolio from 2008Q2 (prior to Lehman's bankruptcy filing) to 2008Q4 (after the bankruptcy filing). To construct this measure, we start with all bonds in the TRACE Enhanced database for which a yield to maturity is available at the end of 2008Q2 and 2008Q4. For each bond, we calculate the yield spread as the difference between the bond's yield to maturity from TRACE Enhanced and the yield to maturity on a maturity-matched Treasury bond from the H.15. Federal Reserve Release.[18] The yield spread change is a bond's yield spread at the end of 2008Q4 minus its yield spread at the end of 2008Q2. We construct each insurer's portfolio yield spread change as the weighted average yield spread change of the corporate bonds in its portfolio. That is,

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

where ΔYS_i is the portfolio yield spread change of insurer i from 2008Q2 to 2008Q4, $\Delta BondYS_{ik}$ is the yield spread change of bond k in its portfolio over the same time period, K is the number

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

of sample bonds held by insurer i at the end of 2007, and w_{ik} is the weight of bond k in insurer i's portfolio, using the par value held at the end of 2007 as the weight. We then construct a pair's joint portfolio yield spread change as the weighted average of each insurer's portfolio yield spread change, using the par value of the bonds held by each insurer as the weight. Specifically,

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

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

Given our previous findings, we expect that when faced with a shock to their assets, pairs with more similar portfolios will experience a larger drop in the value (increase in yield) of their corporate bond holdings than other insurers. That is, we hypothesize that the relationship between a pair's joint portfolio yield spread change and the interaction term *Similarity_I*×*Exposed* will be positive and significant. Our specification also includes as independent variables the weighted average characteristics of the bonds held by the pair measured on the last trade date in the quarter prior to Lehman's bankruptcy: the weighted average of the number of trades in the two quarters prior to the failure (*Ln(Trades)_Avg*), the weighted average of the natural logarithm of the bonds' issuance amount (*Ln(Amount)_Avg*), and the weighted average of the natural logarithm of the bonds' years to maturity (*Ln(Maturity)_Avg*). We also control for the pair's business line, joint size, and portfolio concentration.

The estimation results are presented in Panel B of Table 6. In columns (1) and (3), we find that the coefficient on the interaction term *Similarity_I*×*Exposed* is positive and significant, consistent with our hypothesis. This indicates that the same increase in portfolio similarity increases the joint portfolio yield spread of exposed pairs more than of unexposed pairs. So not only do exposed pairs tend to sell more in common per unit of similarity compared to unexposed pairs (Panel A), but per unit increase in portfolio similarity they also tend to experience a greater drop in the value of their joint bond holdings around the time of Lehman's bankruptcy. When examining the subsample of exposed insurers in columns (2) and (4), we find that the increase in joint portfolio yield spread is greater, the more similar the pair's portfolios.

The effects we document are economically significant as well. For instance, in column (1) we find that for the average pair a 10% increase in *Similarity_I* leads to a 0.49% increase in price impact (i.e., increase in the pair's joint portfolio yield spread). Among exposed pairs the price impact of the same 10% increase in *Similarity_I* is much higher at 4.84%.[19]

6.2 Hurricane Exposure

The landfall of hurricanes Katrina and Rita resulted in $160 billion of total damages according to the National Oceanic and Atmospheric Administration. The impact on the liabilities of P&C insurers was particularly severe with $41 billion of filed claims on personal property, vehicle, and business policies.[20] Since the large number of claims most likely necessitated the sale of securities to cover losses, we use this natural disaster as a shock to the liquidity needs of P&C insurers with significant exposure in the hurricane-affected states.[21] Doing so allows us to minimize the incidence of regular portfolio rebalancing and of selling motivated by changing issuer fundamentals, and to better isolate the effect of portfolio similarity on forced common sales and bond prices.[22]

We collect data for each P&C insurer on the amount of premiums written in the two states most affected by hurricanes Katrina and Rita: Louisiana and Mississippi.[23] We define a pair of insurers as being exposed to potential losses from these hurricanes, *Exposed (hurricanes)*, if both insurers' annual premiums written in hurricane-affected states relative to total premiums written, are in the top quartile of the sample. We capture the timing of the hurricanes with an indicator variable, *Hurricane,* equal to one in 2005Q3, and zero otherwise. We then hypothesize that exposed insurers with more similar portfolios should have larger common sales around the time of the hurricanes.

The estimation results are presented in Panel A of Table 7 and provide evidence consistent with our hypothesis. The coefficient on *Similarity_I*×*Hurricane*×*Exposed* is positive and significant in column (1). When we limit our sample to just exposed insurers in column (2), we find that their

[19] 0.049+0.435=0.484

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

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

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

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

portfolio similarity results in larger common sales during the quarter of the hurricanes than during any other quarter.

Next, we investigate whether bonds held by exposed pairs with greater portfolio similarity experience a larger drop in value around the time of hurricanes Katrina and Rita using a similar approach as in the prior subsection. We adjust the approach for the different timing of the shock. First, the dependent variable is again a pair's joint portfolio yield spread change, but now from 2005Q2 (prior to hurricanes Katrina and Rita) to 2005Q4 (after the hurricanes). Second, we calculate weights using the par value of bonds held at the end of 2004, the year-end before the shock.

The estimation results are presented in Panel B of Table 7. In column (1), we find that the coefficient on the interaction term $\textit{Similarity\_I}\times\textit{Exposed}$ is positive and significant. This indicates that exposed pairs with more similar portfolios experience a larger increase in their joint portfolio's yield spread around the time of the hurricanes compared to other pairs. When examining only the subsample of exposed pairs in column (2), we find that the increase in their joint portfolio's yield spread is greater, the more similar their portfolios.

These findings, based on two very different events, provide evidence that the relationship between portfolio similarity and common sales has the potential to depress prices and affect the value of insurers' holdings. This result holds regardless of whether we examine shocks emanating from within or without the insurance industry. Moreover, our findings demonstrate that events that impact either the asset or liability side of insurers' balance sheets may significantly affect common selling and price impact. Next, we examine whether liability matching and/or asset risk is the driver of our results.

6.3 Shocks and the Effect of Liability Matching and Asset Risk

As discussed in Section 5.2, portfolio similarity can emanate from insurers' asset-liability management and/or risk seeking. Of particular concern to regulators and investors is whether the overlap in holdings of high risk assets, due to insurers' unavoidable similarity in liabilities, results in larger common sales and larger price impact when insurers are faced with a shock. To assess the validity of this concern, we repeat the analyses in Tables 6 and 7 but replace overall portfolio similarity with the four portfolio similarity measures based on liability matching and asset risk analyzed in Table 5. For brevity, we only report the results for exposed insurers, but we note that our findings are robust to including all insurers.

In Panel A of Table 8 we examine the relation between the four portfolio similarities and common sales. As in Table 5, three of the four portfolio similarities carry a positive and significant coefficient, confirming our prior finding that unexpected similarity of low risk assets as well as expected and unexpected similarity of high risk assets all contribute to larger common sales. Interacting the four portfolio similarities with an indicator for the timing of the shock to insurers' assets or liabilities, either the bankruptcy of Lehman or landfall of hurricanes Katrina and Rita, produces mixed results depending on the shock. In columns (1) and (2), exposed pairs with greater expected similarity of high risk assets have larger common sales at the time of Lehman's bankruptcy. This result is consistent with Ellul et al. (2018) who show that some insurers with similar liabilities overweight high risk assets that, in turn, exacerbates fire sales in the event of negative market shocks.

In column (3), where the exogenous shock is the landfall of hurricanes Katrina and Rita, we find the opposite result. Exposed pairs with greater unexpected (expected) similarity of high risk assets have even larger (smaller) common sales.[24] Thus, when there is a shock to liabilities, insurers with similar overinvestment in high risk assets are forced to sell more.

We next investigate the link between the four portfolio similarities and price impact in Panel B. In columns (1) and (2), we document a larger increase in a pair's joint portfolio yield spread around the time of Lehman's bankruptcy, the larger the pair's similarity of high risk assets whether expected or unexpected. We find mixed results when we examine the price impact of a pair's similarity of low risk assets depending on the definition of exposed. In column (3) during hurricanes Katrina and Rita, a pair's unexpected similarity in assets, both high risk and low risk, increases the price impact on the pair's joint portfolio.

Overall, our results highlight the potential impact of similar portfolio allocation strategies that are both related and unrelated to liabilities management, but entail investing in risky assets, to affect common selling and depress prices. A comparison of Tables 6 and 7 to Table 5 suggests that our measure of overall portfolio similarity does a good job of capturing the impact of portfolio

[24] In column (3) the expected portfolio similarity across low risk assets is highly correlated with the expected portfolio similarity of high risk assets, which is why we exclude the former from the specification. This correlation is not surprising since the sample of hurricane exposed pairs is restricted to P&C pairs, which likely have very similar business lines.

similarity of high risk assets on common selling and price impact, which may be particularly useful when the type of future shock is unknown.

7 Individual Insurer Portfolio Similarity

In the previous sections, we provide strong evidence that a pair's portfolio similarity can predict its common sales and resultant price impact. Since our main analysis is at the insurer pair level, isolating individual insurers that may have a greater impact on financial stability through their selling behavior is necessary for monitoring purposes. In this section, we propose a methodology that transforms the portfolio similarity of insurer pairs into a metric at the individual insurer level by averaging an insurer's portfolio similarity with all others in the industry. Specifically, for insurer i at year-end t,

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

where J is the number of insurers. Depending on whether we use asset class or issuer pairwise portfolio similarity, we refer to this measure as average portfolio similarity at the asset class ($Similarity\_Avg\_AC$) or issuer ($Similarity\_Avg\_I$) level.

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

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

Analogously to average portfolio similarity, aggregate common sales are constructed at the asset class ($Common\ Sales\_Aggr\_AC$) or issuer ($Common\ Sales\_Aggr\_I$) level. We then regress this insurer-level measure of aggregate common sales on the insurer's prior year average portfolio similarity at the asset class or issuer level.[25] We also control for the insurer's size ($Size$), concentration of holdings ($Conc\_AC$ or $Conc\_I$), and line of business (PC and $Life$ indicators).

The results are presented in Panel A of Table 9 and indicate that an insurer's $Similarity\_Avg$ is

[25] Our findings remain robust if we use the average of the insurer's common sales.

positively related to its subsequent aggregate common sales. In other words, the more similar the portfolio holdings of a specific insurer to those of other insurers, the more that insurer contributes to common selling in the aggregate. We observe this finding even after controlling for other insurer characteristics such as size, concentration, and business line.[26] In Panel B, we follow a similar methodology as above but using the portfolio similarities of high and low risk assets. Consistent with our prior results, the primary driver of aggregate common sales for individual insurers is the magnitude of their overlap in high risk assets. For large insurers, however, the average portfolio similarity of both high and low risk assets matters in predicting their selling behavior.

We further test whether our ex ante individual insurer measure of potential systemic risk contribution is correlated with another popular systemic risk measure: the ex post conditional covariance risk measure, SRISK.[27] SRISK captures the systemic risk contribution of an individual financial institution by assessing the institution's capital shortfall conditional on market distress (Brownlees and Engle (2017)). Unlike our portfolio similarity measure, it is based on market data, and therefore, can only be calculated for publicly traded insurers. For the subsample of 65 such insurers that are publicly traded every year, we find a positive correlation between SRISK and average portfolio similarity at both the asset class and issuer level.

We also investigate whether lagged values of average portfolio similarity in the pre-crisis years of 2002-2007 are correlated with ex post SRISK in 2008. In untabulated results, we find a positive and statistically significant correlation between the two, indicating that lagged portfolio similarity can predict the systemic risk of insurers reflected in SRISK. These results are compelling, particularly in light of the fact that insurers' portfolio similarity can be calculated even for those insurers that are not publicly traded.

Finally, we examine individual insurers' selling behavior in response to the shocks to assets and liabilities analyzed in Section 6. An open question in the literature is what divestment strategy constrained financial institutions employ. In particular, insurers might employ three different strategies: (a) sell their most liquid holdings first in an attempt to mitigate the price impact of their selling, (b) sell their least liquid holdings first in order to remove impaired assets from their balance sheet, or (c) sell a pro rata share of their investment portfolio. Our data allows us to

[26]Our results are robust to using total net sales instead of total assets to proxy for an insurer's size.
[27]The analysis is available upon request.

answer these questions and furthermore investigate how portfolio similarity factors into the choice of which assets to sell.

We focus our analyses on the selling behavior of the three types of exposed insurers described in Section 6: bank exposed, AIG exposed, and hurricane exposed. We characterize the holdings and sales of these insurers using our primary asset classes and calculate the proportion of the portfolio held in the prior year and sold during the shock year in each of these asset classes. For bank exposed and AIG exposed insurers, the shock is the Lehman bankruptcy filing, so we measure holdings at the end of 2007 and sales during 2008. For hurricane exposed P&C insurers, the shock is the hurricanes Katrina and Rita, so we measure holdings at the end of 2004 and sales during 2005. We use our measure of individual insurer portfolio similarity at the asset class level to classify insurers as having high or low $Similarity\_Avg\_AC$, based on whether it is above or below the median for the year of the reported portfolio holdings. We then examine the holdings and sales of high similarity and low similarity insurers in Table 10.

First, we analyze the overall selling behavior of exposed insurers to understand whether it deviates from their portfolio allocation decision. For example, if insurers are selling a pro rata share of their portfolio, we would expect that each asset class will represent a similar proportion of holdings as it does of sales. In other words, if corporate bonds is 20% of the portfolio and insurers are selling a pro rata share of the portfolio, corporate bonds should account for 20% of sales as well and the difference between the proportion held and proportion sold should be close to zero. If, however, insurers are likely to sell more liquid or illiquid assets first, the proportion sold of these assets will deviate from the proportion held. Generally, we find in Table 10 that when faced with a shock to their balance sheet, insurers are more likely to sell liquid assets such as equity, mutual funds, and US government securities and less likely to sell illiquid assets such as municipal bonds and asset-backed securities.

Next, we examine whether insurers that are characterized as having high portfolio similarity with other insurers display a different selling pattern from that of insurers with low portfolio similarity with other insurers. Irrespective of the shock, high similarity insurers are more likely to sell corporate bonds and less likely to sell GSE securities than low similarity insurers. High similarity insurers exposed to AIG are also more likely to sell mutual funds than low similarity insurers exposed to AIG. Moreover, the propensity for high similarity insurers to sell corporate bonds is consistent with our preceding results that sales by insurers with greater portfolio similarity have a greater impact on corporate bond prices.

8 Regulatory Implications

A number of papers have documented that during times of stress insurers may engage in correlated selling that has spillover effects on the broader economy. The federal regulatory approach after the 2007-2009 financial crisis, for example, has been to identify large insurers that may pose a risk to financial stability and to provide additional oversight of these systemically risky insurers through the Federal Reserve. The process by which insurers have been designated as systemically risky has been criticized not only by academics (Hanley (2016) and Harrington (2016)) but also by the courts. This criticism has lead to the rescission of the SIFI designation of MetLife and subsequently of Prudential and AIG.

Our results highlight the challenges faced by regulators charged with overseeing the insurance industry. The interconnectedness of insurers with other financial institutions (e.g., with banks as shown by Billio et al. (2012)), requires a holistic approach to monitoring financial stability. In particular, because insurer investment decisions are made at the group rather than individual level, our findings indicate that interrelated insurer activities are likely not limited by state borders. Thus, the state focused supervisory approach may be insufficient to fully monitor the financial sector for potential spillovers as it does not address the potential concern that insurers, including small ones, could collectively impose systemic risks on the broader economy due the similarity of their portfolios.

Moreover, in our opinion, the bifurcation of regulation between SIFI designated and non-designated firms both within and without the insurance industry may be problematic and should be reconsidered. This approach could create regulatory "cliffs" where two relatively similar firms do not compete on a "level playing field" because one is designated and the other is not, for example on the basis of size. There are a number of alternate regulatory schemes that may better accomplish the goal of monitoring insurance company activities and the potential for insurers to contribute to contagion in the financial sector.

First, the monitoring of insurer activities that contribute to financial instability needs to be done at the federal, rather than at the state level. Currently, insurers are regulated at the state level with the NAIC as "the U.S. standard-setting and regulatory support organization created and governed by the chief insurance regulators from the 50 states, the District of Columbia and five U.S. territories." Whether federal monitoring could be achieved by expanding the role of the NAIC (or the International Association of Insurance Supervisors) or through the formation of a national insurance regulator, similar to the Securities and Exchange Commission, is unclear but should be debated. The federal oversight we envision should include stress testing the portfolios of insurers under certain macroeconomic and liquidity scenarios to understand their ability to withstand market stress.[28] Although the Dodd-Frank Act created the Federal Insurance Office to inform Congress on insurance matters, the Office has no formal regulatory authority to provide prudential systemic supervision of insurers.

Second, the monitoring of the insurance sector cannot be done in isolation as banks, insurers, and other financial institutions are interconnected (Billio et al. (2012)). Such holistic monitoring could be performed by the FSOC and Office of Financial Research, whose mission is to help promote financial stability, in cooperation with banking regulators and the NAIC.

Third, the understanding gained from the analyses of insurance activities should inform the new FSOC activity-based policy approach to monitoring insurers. For example, investment in illiquid and/or risky assets is an insurer activity that may require additional oversight. However, we acknowledge that because of asset-liability matching, some degree of portfolio similarity and hence correlated selling may be difficult to avoid. Furthermore, a policy response that restricts or limits insurer investment choices could result in inefficient portfolio allocation and therefore, regulators face a difficult tradeoff.

9 Conclusion

While the literature on systemic risk has traditionally focused on financial institutions' funding vulnerabilities, attention has recently shifted, particularly for non-bank financial institutions, towards asset interconnectedness. The concern is that financial institutions holding similar assets

[28]The International Association of Insurance Supervisors has identified liquidity risk as one potential activity to be monitored more closely. See https://www.naic.org/insurance_summit/documents/insurance_summit_2018_FR_34-3.pdf.

as a result of their shared business model may jointly liquidate these assets and negatively impact prices.

In this paper, we investigate the validity of this concern. We develop a novel measure of pairwise interconnectedness that focuses on insurers' portfolio similarity. We examine the measure's association with common selling and find that pairs of insurers that have greater portfolio similarity have larger subsequent common sales. This result holds across all insurer pairs regardless of their size.

To better understand why portfolio similarity increases common sales and whether this positive relation should be a concern, we separately calculate a pair's portfolio similarity across high-risk and low-risk assets. We then decompose these two portfolio similarity measures into their expected and unexpected portions given the pair's liability similarity. We find that the expected portion of high risk portfolio similarity contributes most to common sales. In contrast, the expected portfolio similarity across low risk assets is negatively, not positively related to common sales. Collectively, these results indicate that the overlap in high risk assets associated with asset-liability management may exacerbate common sales. This suggests that restricting such investments may result in inefficient asset allocation, making it challenging to reduce common sales in times of market stress.

We examine whether forced selling either due to a shock to the asset or liability side of insurers' balance sheets affects asset prices by exploiting two events: the bankruptcy of Lehman and the landfall of hurricanes Katrina and Rita. We find that in response to these shocks, insurers with large exposures to the bank debt, AIG, or hurricane-affected states have even greater common sales when they have greater portfolio similarity. Using corporate bond price information, we also show that these insurers' holdings experience a decline in value from the quarter before to the quarter after the shocks and that this drop is larger when exposed insurers have more similar portfolios.

Finally, we use the average portfolio similarity of an individual insurer with all others in the industry as a way to gauge its potential to contribute to financial instability. We show that while insurer characteristics such as size and portfolio concentration affect an insurer's aggregate common sales, its average portfolio similarity remains a significant predictor. Furthermore, the average overlap in high risk assets but not the average overlap in low risk assets predicts common selling for smaller insurers. These results confirm that similarity in the holdings of high risk assets could exacerbate correlated selling in times of financial instability.

Although the portfolio similarity of high risk assets is the primary driver of our results, to construct such a similarity one must classify each asset as high or low risk. While certainly doable, doing so is non-trivial and may create perverse investment incentives for insurers, similar to those linked to risk-based capital requirements (e.g., Becker and Ivashina (2015)). Thus, we propose that the overall measure of portfolio similarity is the most efficient way to predict common selling and price impact.

Overall, our results indicate that commonality in asset holdings captures important mechanics of the asset liquidation channel of systemic risk transmission in the insurance industry. Specifically, the portfolio similarity measure we develop can predict the probability and magnitude of common selling of similar asset classes and similar issuers that may negatively affect prices. Furthermore, our measure captures similarity across the entirety of financial institutions' portfolios and does not require that institutions have publicly traded equity as is the case with other common systemic risk measures. Thus, we believe that our portfolio similarity measure can be used by regulators to predict the common selling of any institution that reports security or asset class level holdings. Along side other indicators, it could serve an an ex-ante measure of systemic risk steaming from the collective divestment decisions of financial institutions.

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Appendix A: Asset Classes

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

Appendix B: Variable Definitions

Variable	Definition
Common Sales_Aggr_AC or Common Sales_Aggr_I	The sum of an insurer's common sales with all other insurers, at the asset class (AC) or issuer (I) level.
Common Sales_AC or Common Sales_I	The dot product of an insurer pair's net dollar sales vectors at the asset class (AC) or issuer (I) level.
Conc_AC or Conc_I	Asset class (AC) or issuer(I) level Herfindahl index of an insurer's portfolio: $Conc_{it} = \sum_{k=1}^{K} w_{itk}^2$ where w_{itk} is asset class/issuer k's proportion in insurer i's portfolio at the end of year t. Asset class/issuer level proportions are calculated as the dollar amount invested in each asset class/issuer relative to the total value of the insurer portfolio.
Crisis	An indicator variable equal to one for the years 2007, 2008, and 2009; 0 otherwise.
Exposed (bank debt)	An indicator variable equal to one if the annual dollar-valued proportion of financial firm bonds held to total bonds held is in the top quartile of the sample for the year for both insurers in a pair, and zero otherwise.
Exposed (AIG)	An indicator variable equal to one if the portfolio similarity with AIG is above the median for the sample for both insurers in a pair, and zero otherwise.
Exposed (hurricanes)	An indicator variable equal to one if the annual proportion of Louisiana and Mississippi premiums written to total premiums written is in the top quartile of the sample for both insurers in a pair, and zero otherwise.
Hurricane	An indicator variable equal to one in 2005Q3, and zero otherwise.
Joint portfolio yield spread change (bank debt and AIG)	Weighted average of a pair's portfolio yield spread changes, using 2007 corporate bond par value held as the weight. Portfolio yield spread change is the weighted average of an insurer's corporate bond yield spread changes, using each bond's 2007 par value held as the weight. A bond's yield spread change is its yield spread at the end of 2008Q4 minus that at the end of 2008Q2, where a yield spread is a bond's yield to maturity minus that on a maturity-matched Treasury.
Joint portfolio yield spread change (hurricanes)	Weighted average of a pair's portfolio yield spread changes, using 2004 corporate bond par value held as the weight. Portfolio yield spread change is the weighted average of an insurer's corporate bond yield spread changes, using each bond's 2004 par value held as the weight. A bond's yield spread change is its yield spread at the end of 2005Q4 minus that at the end of 2005Q2, where a yield spread is a bond's yield to maturity minus that on a maturity-matched Treasury.
Large	An indicator variable equal to one if an insurer has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period, and zero otherwise.
Large_Pair	An indicator variable equal to one if Large=1 for both insurers in a pair, and zero otherwise.
Lehman	An indicator variable equal to one in 2008Q3 and 2008Q4, and zero otherwise.
Life	An indicator variable equal to one 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, and zero otherwise.
Life_Pair	An indicator variable equal to one if Life=1 for both insurers in a pair, and zero otherwise.
Ln(Amount)_Avg	Weighted average of the natural logarithm of the issuance amount of the corporate bonds held by a pair.
Ln(Maturity)_Avg	Weighted average of the natural logarithm of the years to maturity of the corporate bonds held by a pair.
Ln(Trades)_Avg	Weighted average of the natural logarithm of the 2005Q1–2005Q2 number of trades of the corporate bonds held by a pair.
PC	An indicator variable equal to one 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, and zero otherwise.
PC_Pair	An indicator variable equal to one if PC=1 for both insurers in a pair, and zero otherwise.
PostCrisis	An indicator variable equal to one for the years 2010 to 2014, and zero otherwise.
Prod_Conc_AC or Prod_Conc_I	The product of Conc_AC or Conc_I for an insurer pair.
Prod_Size	The natural logarithm of the product of portfolio assets for an insurer pair.

Variable	Definition
Similarity_AC or Similarity_I	The cosine similarity between a pair of insurers' asset class (AC) or issuer (I) portfolio weights.
Similarity_Avg_AC or Similarity_Avg_I	A simple average of an insurer's portfolio similarities with all other insurers, at the asset class (AC) or issuer (I) level.
Similarity_AC_Exp	The fitted values from a regression of Similarity_AC on business line similarity, Life_Pair, PC_Pair, and year-quarter fixed effects.
Similarity_AC_HighRisk	Similarity_AC constructed using only assets that have high potential tail risk: all private offerings, RMBS, CMBS, ABS, and other fixed-income securities with NAIC designation of 2 or higher.
Similarity_AC_HighRisk_Exp	The fitted values from a regression of Similarity_AC_HighRisk on business line similarity, Life_Pair, PC_Pair, and year-quarter fixed effects.
Similarity_AC_HighRisk_Unexp	The residuals from a regression of Similarity_AC_HighRisk on business line similarity, Life_Pair, PC_Pair, and year-quarter fixed effects.
Similarity_AC_LowRisk	Similarity_AC constructed using only assets that have low potential tail risk: equities, mutual fund shares, and fixed-income securities (other than private offerings, RMBS, CMBS, and ABS) with NAIC designation of 1.
Similarity_AC_LowRisk_Exp	The fitted values from a regression of Similarity_AC_LowRisk on business line similarity, Life_Pair, PC_Pair, and year-quarter fixed effects.
Similarity_AC_LowRisk_Unexp	The residuals from a regression of Similarity_AC_LowRisk on business line similarity, Life_Pair, PC_Pair, and year-quarter fixed effects.
Similarity_AC_Unexp	The residuals from a regression of Similarity_AC on business line similarity, Life_Pair, PC_Pair, and year-quarter fixed effects.
Size	The natural logarithm of an insurer's portfolio assets.
Total_Sales_AC or Total_Sales_I	The natural logarithm of an insurer's total net sales at the asset class (AC) or issuer (I) level.

Appendix C: Cluster Analysis

Cluster Algorithm

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

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

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

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

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

We run the unsupervised *K-means* algorithm (MacQueen, 1967) yearly with the following setting:[29]

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

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

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

We then analyze the clusters by examining:

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

ii) their centroids' structure;

iii) the transition of insurers among clusters over time.

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

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

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

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

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

The cluster validation process applied to the yearly dataset provides the best fitting algorithm for the number of clusters. Each validation methodology is applied yearly using *K-means* algorithm. The optimal number of clusters appears to be 3.[30]

Cluster Validation

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Figure 1. Portfolio composition through time

This figure presents the year-end composition of the aggregate insurance industry portfolio by primary asset class. The sample period is 2002-2014.

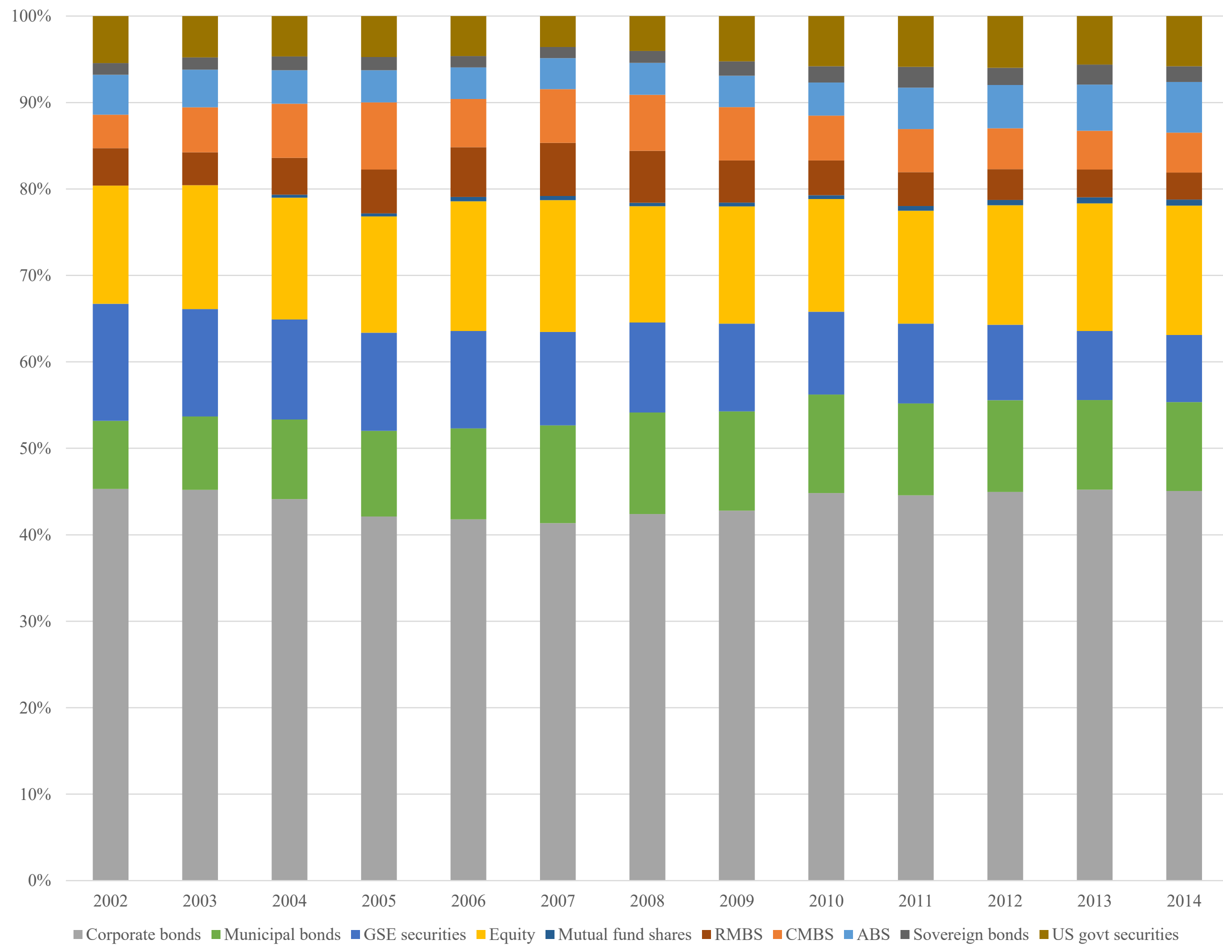


Figure 2. Portfolio cluster composition by primary asset classes

This figure presents the average primary asset class dollar composition of the three clusters of year-end insurer portfolios. The sample period is 2002-2014.

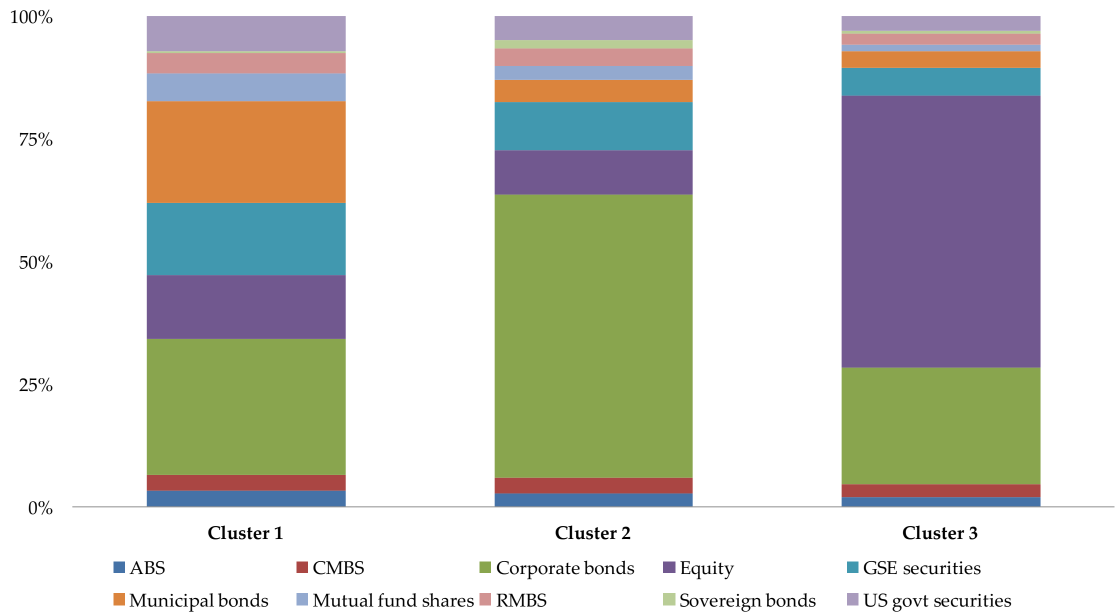
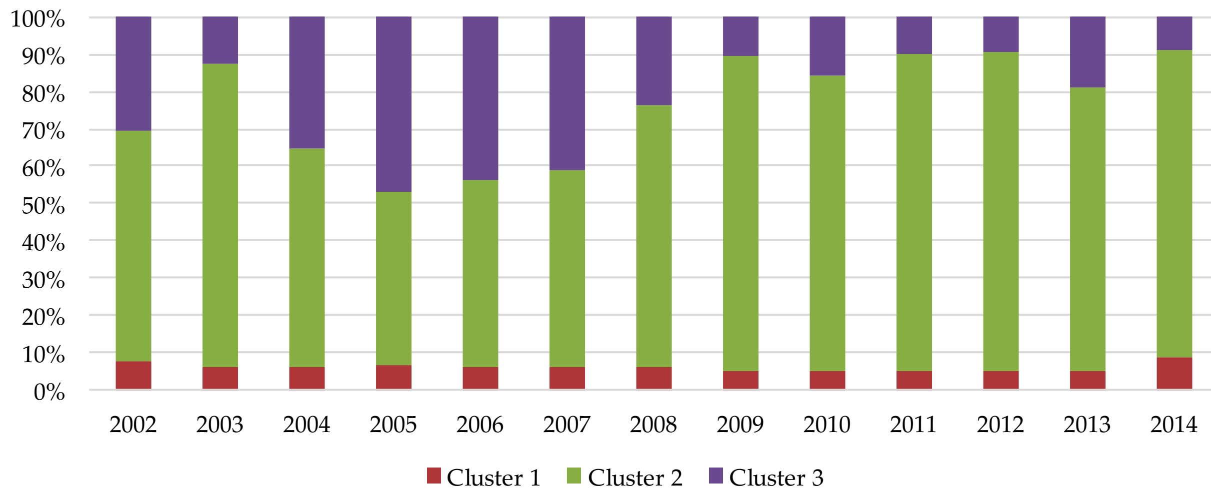
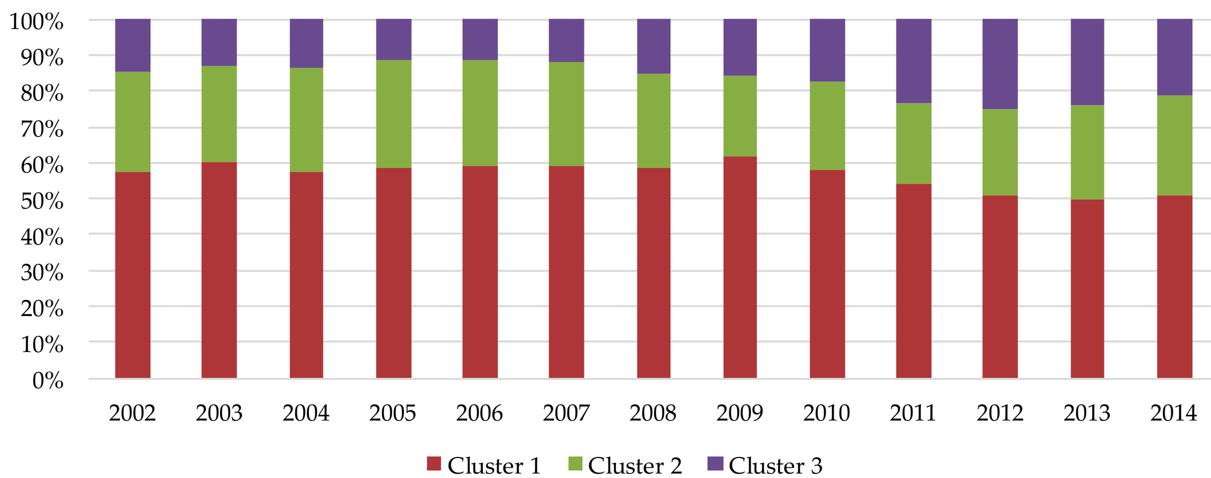


Figure 3. Distribution of large and all other insurers in portfolio clusters

The figures present the distribution of large and all other insurers among the three clusters. A large insurer is one that has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. All other insurers exclude large insurers. The sample period is 2002-2014.



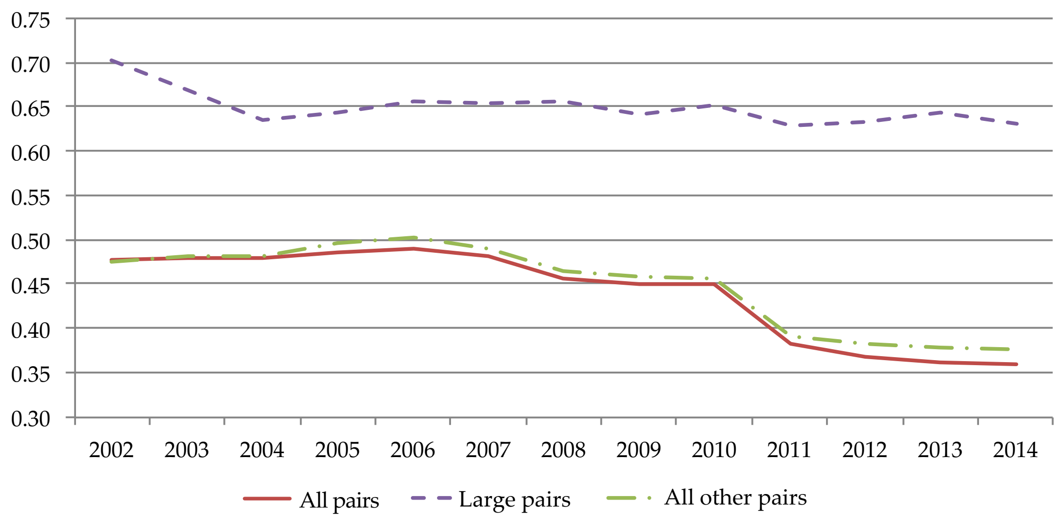
(a) Large insurers



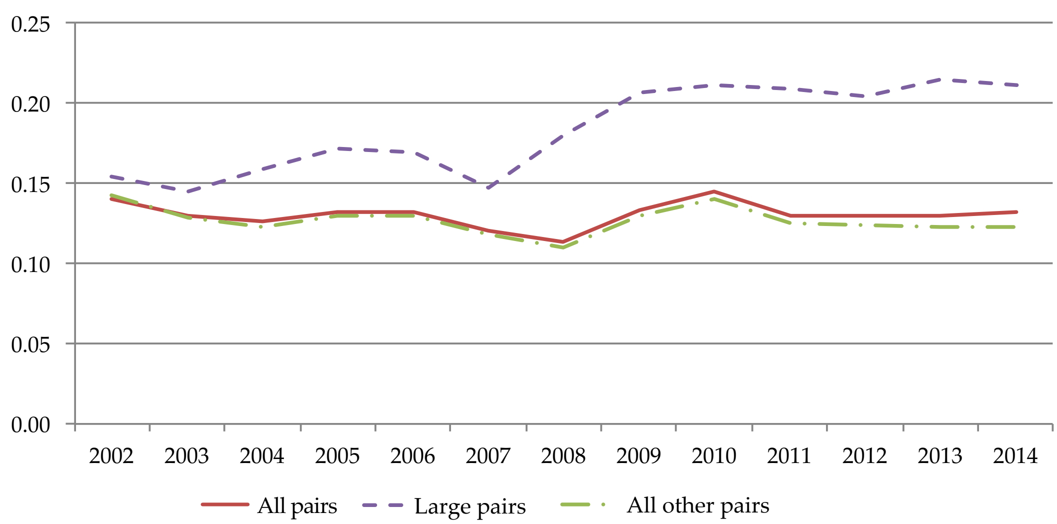
(b) All other insurers

Figure 4. Portfolio similarity through time

The figure presents average portfolio similarity at the (a) asset class level ($Similarity\_AC$) and (b) issuer level ($Similarity\_I$). Large insurer pairs are those in which both insurers are large, defined as having $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. All other insurer pairs are those in which neither insurer is large. The sample period is 2002-2014.



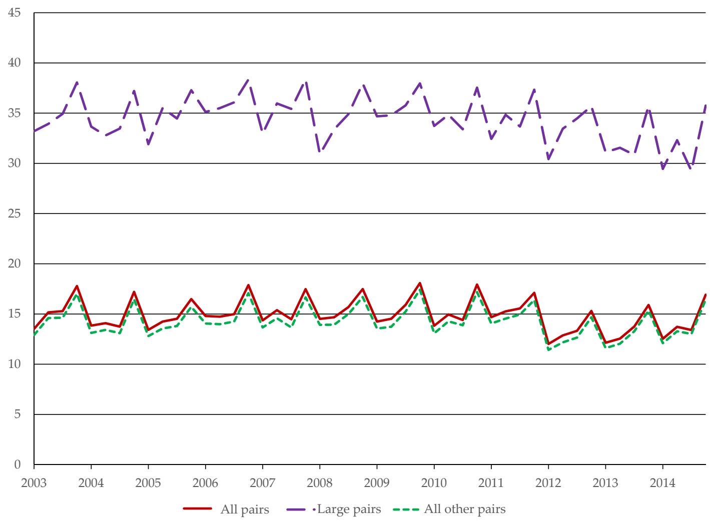
(a) Portfolio Similarity at the Asset Class Level



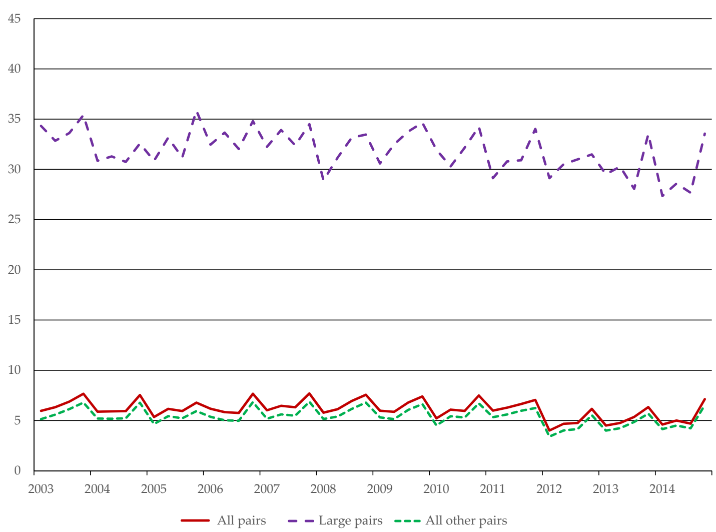
(b) Portfolio Similarity at the Issuer Level

Figure 5. Common sales through time

The figures present the average of the natural logarithm of one plus quarterly common sales at the (a) asset class level ($Common\,Sales\_AC$) or (b) issuer level ($Common\,Sales\_I$). Large insurer pairs are those in which both insurers are large, defined as having \$50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. All other insurer pairs are those in which neither insurer is large. The sample period is 2002-2014.



(a) Common Sales at the Asset Class Level



(b) Common Sales at the Issuer Level

Table 1: Portfolio composition and other insurer characteristics

The table presents statistics on portfolio composition and other characteristics for all, life, P&C, and large insurers during 2002-2014. Life insurers operate predominantly in life lines of business. P&C insurers operate predominantly in property and casualty lines of business. Large insurers have $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. Investment portfolio is the dollar value of portfolio holdings disclosed on Schedule D. Corporate bonds, GSE debt securities, municipal bonds, U.S. government securities, RMBS, CMBS, ABS, sovereign bonds, equity, and mutual fund shares are the dollar-value percentages of an insurer's portfolio invested in these primary asset classes. Number of issues is the number of unique 9-digit CUSIPs in an insurer's portfolio. Number of issuers is the number of unique issuers, identified using 6-digit CUSIPs in an insurer's portfolio. *Conc_AC* or *Conc_I* is a Herfindahl index constructed for each insurer as the sum of the squared weights of asset classes or issuers in its portfolio. Asset class/issuer weights are calculated as the dollar amount invested in each asset class/issuer relative to the total value of an insurer's portfolio. Mean, medians and standard deviations are based on the cross-sectional variation of insurers' time series average.

	All (N=2,812)			Life (N=635)			P&C (N=1,746)			Large (N=38)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Insurer characteristics ($B)												
Total assets incl separate accounts	3.25	0.06	23.30	11.19	0.08	47.25	0.85	0.05	4.20	145.12	87.70	117.39
Total assets excl separate accounts	2.41	0.06	15.42	7.54	0.08	30.67	0.85	0.05	4.20	99.80	67.89	71.84
Investment portfolio	1.65	0.04	10.46	5.04	0.07	19.75	0.89	0.03	6.18	36.63	30.08	24.60
Primary asset class composition (%)												
Corporate bonds	27.1	24.1	22.3	36.4	36.7	24.0	23.7	21.4	19.4	52.7	56.9	18.4
GSE debt securities	19.3	15.4	19.3	20.7	15.4	20.1	19.2	15.9	18.6	12.1	8.2	12.7
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
U.S. government securities	15.4	5.8	23.8	14.2	3.9	24.9	14.8	6.1	21.8	3.2	0.9	4.4
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
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
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
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
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
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
Issue/Issuer composition												
Number of issues	380	116	1,074	748	174	1,790	291	111	812	3,704	3,204	2,661
Number of issuers	250	100	493	440	137	809	203	97	363	1,888	1,705	922
Concentration												
Conc_AC	0.31	0.20	0.26	0.28	0.16	0.26	0.30	0.20	0.24	0.12	0.10	0.08
Conc_I	0.16	0.04	0.25	0.14	0.03	0.25	0.14	0.04	0.22	0.01	0.00	0.02

Table 2: Summary statistics for portfolio similarity and common sales

The table presents summary statistics for portfolio similarity and common sales of all and large insurer pairs during 2002-2014. Large pairs are those in which both insurers are large, defined as having $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. *Similarity_AC* or *Similarity_I* is the cosine similarity between a pair's asset class or issuer portfolio weights. *Common Sales_AC* or *Common Sales_I* is the dot product of a pair's asset class or issuer level net sales. P25, P50 and P75 indicate the 25th, 50th, and 75th percentile of the distribution.

	All					Large				
	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
Similarity_AC	0.45	0.27	0.22	0.45	0.68	0.65	0.22	0.52	0.70	0.82
Similarity_I	0.12	0.18	0.01	0.05	0.15	0.18	0.15	0.07	0.14	0.26
Ln(1+Common Sales_AC)	14.92	13.84	0.00	21.96	27.67	34.42	7.93	33.85	36.04	37.98
Ln(1+Common Sales_I)	6.07	11.32	0.00	0.00	0.00	31.89	9.66	32.34	34.42	36.08

Table 3: Determinants of Portfolio Similarity

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

	Asset class		Issuer	
	All	Large	All	Large
	(1)	(2)	(3)	(4)
Life_Pair	0.053***	0.183***	-0.006***	0.027***
	(7.44)	(21.48)	(-3.94)	(3.69)
PC_Pair	0.039***	0.087***	0.029***	0.035**
	(9.21)	(7.16)	(23.51)	(2.30)
Large_Pair	0.006		0.040***	
	(0.80)		(7.46)	
Prod_Size	0.013***	-0.020***	0.003***	0.005
	(16.97)	(-3.55)	(5.24)	(1.03)
Prod_Conc_AC	-0.355***	-22.250***		
	(-17.73)	(-8.73)		
Prod_Conc_I			0.575***	-111.707***
			(14.48)	(-7.12)
Year FE	YES	YES	YES	YES
N	10,605,950	6,608	10,605,950	6,608
Adj R^2	0.098	0.436	0.029	0.064

Table 4: Portfolio Similarity as a Determinant of Common Sales

The table presents probit/tobit estimation results for all and large insurer pairs during 2002-2014. Large pairs are those in which both insurers are large, defined as having $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. In columns (1) and (4), the dependent variable is an indicator equal to one if the natural logarithm of one plus *Common Sales_AC* or *Common Sales_I*, defined as the dot product of a pair's asset class or issuer net sales, is positive, and zero otherwise. In columns (2)–(3) and (5)–(6) the dependent variable is the natural logarithm of one plus *Common Sales_AC* or *Common Sales_I*. *Similarity_AC* or *Similarity_I* is the cosine similarity between a pair's asset class or issuer portfolio weights. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. t-statistics that use standard errors clustered by year-quarter are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	Asset class			Issuer		
	All Probit (1)	All Tobit (2)	Large Tobit (3)	All Probit (4)	All Tobit (5)	Large Tobit (6)
Similarity_AC	0.233***	4.551***	4.640***			
	(26.68)	(23.20)	(7.38)			
Similarity_I				1.102***	34.057***	17.628***
				(44.68)	(40.60)	(19.87)
Life_Pair	-0.117***	-2.173***	-0.515**	-0.112***	-3.341***	0.586***
	(-13.70)	(-13.41)	(-2.15)	(-11.28)	(-11.73)	(3.03)
PC_Pair	0.134***	2.536***	0.419	0.117***	3.448***	0.008
	(24.87)	(21.87)	(1.10)	(18.36)	(18.82)	(0.02)
Large_Pair	0.626***	2.782***		0.716***	4.117***	
	(15.97)	(9.67)		(31.64)	(8.38)	
Prod_Size	0.085***	1.973***	1.200***	0.139***	4.401***	1.387***
	(44.47)	(66.01)	(12.00)	(56.68)	(72.26)	(9.80)
Prod_Conc_AC	-3.287***	-64.996***	-13.910			
	(-28.76)	(-26.58)	(-0.46)			
Prod_Conc_I				-1.617***	-39.224***	-7,669.241***
				(-4.14)	(-3.44)	(-7.22)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
N	18,247,630	18,247,630	23,440	18,940,884	18,940,884	23,564
Pseudo R^2	0.067	0.024	0.018	0.114	0.046	0.025

Table 5: Common Sales and the Effect of Liabilities Matching and Asset Risk

The table presents probit/tobit estimation results for all and large insurer pairs during 2002-2014. Large pairs are those in which both insurers are large, defined as having $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. In column (1), the dependent variable is an indicator variable equal to one if the natural logarithm of one plus *Common Sales_AC*, defined as the dot product of a pair's asset class net sales, is positive, and zero otherwise. In columns (2)–(3)), the dependent variable is the natural logarithm of one plus *Common Sales_AC*. *Similarity_AC_HighRisk* and *Similarity_AC_LowRisk* are a pair's asset class portfolio similarity constructed using only assets with high and low potential tail risk, respectively. *Similarity_AC_HighRisk_Exp* and *Similarity_AC_HighRisk_Unexp* are a pair's expected and unexpected asset class portfolio similarity across assets with high potential tail risk, constructed as the fitted and residual values from regressions of *Similarity_AC_HighRisk* on the pair's business line similarity. *Similarity_AC_LowRisk_Exp* and *Similarity_AC_LowRisk_Unexp* are a pair's expected and unexpected asset-class portfolio similarity across assets with low potential tail risk, constructed as the fitted and residual values from regressions of *Similarity_AC_LowRisk* on the pair's business line similarity. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. t-statistics that use standard errors clustered by year-quarter are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	All Probit (1)	All Tobit (2)	Large Tobit (3)
Similarity_AC_LowRisk_Exp	-0.126***	-2.241***	-4.846***
	(-112.03)	(-110.74)	(-9.00)
Similarity_AC_LowRisk_Unexp	0.038***	0.724***	0.893***
	(13.75)	(14.23)	(5.48)
Similarity_AC_HighRisk_Exp	0.193***	3.263***	8.171***
	(39.32)	(34.77)	(8.95)
Similarity_AC_HighRisk_Unexp	0.045***	0.790***	0.949***
	(16.42)	(15.26)	(4.66)
Life_Pair	-0.433***	-7.220***	-9.269***
	(-23.72)	(-21.06)	(-8.90)
PC_Pair	0.264***	4.633***	-10.399***
	(36.73)	(32.03)	(-7.51)
Large_Pair	0.566***	1.960***	
	(13.93)	(7.36)	
Prod_Size	0.085***	1.929***	1.226***
	(43.65)	(64.55)	(12.23)
Prod_Conc_AC	-4.399***	-85.348***	-22.304
	(-31.34)	(-28.44)	(-0.75)
Year-Quarter FE	YES	YES	YES
N	14,406,393	14,406,393	23,440
Pseudo R^2	0.068	0.023	0.019

Table 6: Bank and AIG Exposures

The table presents tobit (Panel A) and cross-sectional OLS (Panel B) estimation results for all insurer pairs. In Panel A, the sample period is 2002-2014 and the dependent variable is the natural logarithm of one plus *Common Sales_I*, defined as the dot product of a pair's issuer net sales. *Similarity_I* is the cosine similarity between a pair's issuer portfolio weights. *Lehman* is an indicator variable equal to one in the third and fourth quarters of 2008 corresponding to the Lehman's bankruptcy filing, and zero otherwise. In columns (1)–(2), *Exposed* is an indicator variable equal to one if both insurers' portfolio holdings of financial firms' bonds relative to all corporate bonds are in the top quartile of the sample for the year, and zero otherwise. In columns (3)–(4), *Exposed* is an indicator variable equal to one if both insurers' portfolio similarity with AIG at the issuer level is above the median level of the sample in that year, and zero otherwise. In Panel B, the dependent variable is a pair's joint portfolio yield spread change from 2008Q2 (prior to Lehman's bankruptcy filing) to 2008Q4 (after the filing), defined as the weighted average of the insurers in the pair's portfolio yield spread change, using the par value of the bonds held by each insurer at the end of 2007 as the weight. The yield spread change of a bond is its yield spread at the end of 2008Q4 minus its yield spread at the end of 2008Q2, where a yield spread is the bond's yield minus the yield on a maturity-matched Treasury. *Ln(Trades)_Avg* is the weighted average of the number of trades in the two quarters prior to Lehman's bankruptcy filing. *Ln(Amount)_Avg* is the weighted average of the natural logarithm of the bonds' issuance amount. *Ln(Maturity)_Avg* is the weighted average of the natural logarithm of the bond's years to maturity. The remaining independent variables are defined in Appendix B. All independent variables are measured at the year end prior to the sales quarter in Panel A and at the end of 2007 in Panel B. *t*-statistics, that use standard errors clustered by year-quarter in Panel A, are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

Panel A. Common sales - issuer

	Bank exposed		AIG exposed	
	All	Exposed	All	Exposed
	(1)	(2)	(3)	(4)
Similarity_I	34.582***	29.274***	31.666***	29.179***
	(39.86)	(20.60)	(21.95)	(33.07)
Similarity_I×Lehman×Exposed	4.684***		11.539***	
	(4.31)		(5.14)	
Similarity_I×Lehman	0.192	4.077*	-3.987	5.238***
	(0.11)	(1.86)	(-1.21)	(2.83)
Similarity_I×Exposed	-9.429***		-4.039**	
	(-8.86)		(-2.25)	
Lehman×Exposed	-3.165***		-0.524	
	(-5.39)		(-0.72)	
Lehman	4.595***	7.475***	4.454***	1.964***
	(17.26)	(17.10)	(23.56)	(5.88)
Exposed	0.558		4.255***	
	(1.40)		(15.13)	
Life_Pair	-3.287***	-4.301***	-3.462***	-3.272***
	(-11.66)	(-4.29)	(-12.59)	(-10.59)
PC_Pair	3.471***	0.317	3.755***	2.744***
	(19.20)	(0.55)	(20.82)	(11.18)
Prod_Size	4.400***	3.716***	4.300***	4.350***
	(74.48)	(31.37)	(80.59)	(99.35)
Prod_Conc_I	-38.152***	-89.158***	-23.332**	-3.636
	(-3.37)	(-3.28)	(-2.36)	(-0.32)
Year-Quarter FE	YES	YES	YES	YES
N	18,940,884	1,010,235	18,908,222	6,015,013
Pseudo R^2	0.046	0.022	0.046	0.042

Panel B. Price impact

	Bank exposed		AIG exposed	
	All	Exposed	All	Exposed
	(1)	(2)	(3)	(4)
Similarity_I	0.049***	0.327***	0.079***	0.123***
	(5.848)	(9.684)	(6.867)	(11.374)
Similarity_I×Exposed	0.435***		0.166***	
	(15.905)		(10.311)	
Exposed	-0.084***		-0.097***	
	(-14.195)		(-30.461)	
Avg. Ln(Amount)	-0.093***	-0.615***	-0.085***	0.130***
	(-30.928)	(-52.038)	(-28.416)	(23.084)
Avg. Ln(Maturity)	0.205***	0.214***	0.205***	0.070***
	(61.276)	(15.125)	(61.422)	(14.066)
Avg. Ln(Trades)	-0.401***	0.170***	-0.406***	-0.554***
	(-143.714)	(13.707)	(-146.607)	(-127.255)
Life_Pair	-0.002	0.116**	-0.002	-0.017***
	(-0.542)	(2.225)	(-0.370)	(-2.983)
PC_Pair	-0.066***	-0.047***	-0.073***	-0.126***
	(-26.363)	(-3.780)	(-29.099)	(-35.982)
Prod_Size	0.021***	0.000	0.023***	0.018***
	(53.739)	(0.138)	(59.395)	(32.860)
Prod_Conc_I	1.330***	1.915**	0.944***	38.413***
	(6.606)	(2.434)	(4.580)	(28.867)
Constant	5.581***	9.598***	5.426***	3.763***
	(171.967)	(86.602)	(166.453)	(61.616)
N	423,079	27,328	422,151	163,775
Adj. R^2	0.233	0.206	0.234	0.278

Table 7: Hurricane Exposure

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

Panel A. Common sales - issuer

	All (1)	Exposed (2)
Similarity_I	28.252***	30.044***
	(36.04)	(22.15)
Similarity_I×Hurricane×Exposed	6.416***	
	(5.80)	
Similarity_I×Hurricane	0.399	5.254***
	(0.57)	(3.98)
Similarity_I×Exposed	2.006*	
	(1.88)	
Hurricane×Exposed	1.822***	
	(4.99)	
Hurricane	-1.011***	-0.366
	(-7.93)	(-1.55)
Exposed	-2.021***	
	(-6.50)	
Prod_Size	4.182***	4.214***
	(63.00)	(52.85)
Prod_Conc_I	-40.656***	-103.693**
	(-3.35)	(-2.39)
Year-Quarter FE	YES	YES
N	9,368,378	657,504
Pseudo R^2	0.036	0.042

Panel B. Price impact

	All (1)	Exposed (2)
Similarity_I	-0.067***	0.145***
	(-10.050)	(6.557)
Similarity_I×Exposed	0.089***	
	(3.856)	
Exposed	-0.002	
	(-0.402)	
Avg. Ln(Amount)	-0.140***	-0.153***
	(-68.148)	(-10.454)
Avg. Ln(Maturity)	0.052***	0.127***
	(18.638)	(12.144)
Avg. Ln(Trades)	0.168***	0.093***
	(82.109)	(9.856)
Prod_Size	-0.016***	-0.028***
	(-42.918)	(-21.990)
Prod_Conc_I	-6.380***	-43.641***
	(-25.776)	(-29.718)
Constant	1.535***	2.515***
	(67.755)	(16.393)
N	200,616	15,156
Adj. R^2	0.066	0.097

Table 8: Shocks and the Effect of Liability Matching and Asset Risk

The table presents tobit (Panel A) and cross-sectional OLS (Panel B) estimation results for exposed insurer pairs. In column (1), a pair is bank exposed if both insurers' portfolio holdings of financial firms' bonds relative to all corporate bonds are in the top quartile of the sample for the year. In column (2), a pair is AIG exposed if both insurers' portfolio similarity with AIG at the issuer level is above the median level of the sample in that year. In column (3), a P&C pair is hurricane exposed if both P&C insurers' premiums written in affected states (Mississippi and Louisiana) relative to all premiums written, are in the top quartile of the sample for the year. In Panel A, the dependent variable is the natural logarithm of one plus *Common Sales_AC*, defined as the dot product of a pair's asset class net sales. In Panel B, the dependent variable is a pair's joint portfolio yield spread change from the second to the fourth quarter of 2008 in columns (1) and (2) and 2005 in column (3), defined as the weighted average of the insurers in the pair's portfolio yield spread change, using the par value of the bonds held by each insurer at the end of 2007 and 2004, respectively, as the weight. *Similarity_AC_HighRisk* and *Similarity_AC_LowRisk* are a pair's asset class portfolio similarity constructed using only assets with high and low potential tail risk, respectively. *Similarity_AC_HighRisk_Exp* and *Similarity_AC_HighRisk_Unexp* are a pair's expected and unexpected asset class portfolio similarity across assets with high potential tail risk, constructed as the fitted and residual values from regressions of *Similarity_AC_HighRisk* on the pair's business line similarity. *Similarity_AC_LowRisk_Exp* and *Similarity_AC_LowRisk_Unexp* are a pair's expected and unexpected asset-class portfolio similarity across assets with low potential tail risk, constructed as the fitted and residual values from regressions of *Similarity_AC_LowRisk* on the pair's business line similarity. *Shock* is an indicator variable equal to one during the third and fourth quarters of 2008 in columns (1) and (2), and during the third quarter of 2005 in column (3), and zero otherwise. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. *t*-statistics that use standard errors clustered by year-quarter are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

Panel A: Common sales

	Bank Exposed (1)	AIG Exposed (2)	Hurricane Exposed (3)
Similarity_AC_LowRisk_Exp	-3.529***	-1.497***	
	(-55.95)	(-39.81)	
Similarity_AC_LowRisk_Exp×Shock	-8.533***	-3.117***	
	(-5.42)	(-6.19)	
Similarity_AC_LowRisk_Unexp	0.830***	0.609***	0.364***
	(9.92)	(8.35)	(3.60)
Similarity_AC_LowRisk_Unexp×Shock	0.420	-0.220***	0.134
	(1.10)	(-3.07)	(1.32)
Similarity_AC_HighRisk_Exp	4.876***	2.626***	0.589***
	(21.23)	(22.84)	(4.75)
Similarity_AC_HighRisk_Exp×Shock	5.564***	2.110***	-0.949***
	(2.97)	(5.06)	(-7.54)
Similarity_AC_HighRisk_Unexp	0.791***	0.680***	0.321***
	(11.33)	(9.53)	(3.69)
Similarity_AC_HighRisk_Unexp×Shock	-0.874***	-0.219	1.373***
	(-3.58)	(-0.54)	(15.20)
Shock	9.675***	5.624***	-0.768***
	(7.37)	(16.23)	(-15.36)
Life_Pair	-9.141***	-7.281***	
	(-9.03)	(-16.60)	
PC_Pair	4.444***	4.670***	
	(9.49)	(24.49)	
Prod_Size	1.587***	1.974***	1.968***
	(24.41)	(66.18)	(42.44)
Prod_Conc_AC	-69.303***	-138.117***	-105.870***
	(-15.58)	(-14.16)	(-18.72)
N	715,654	4,772,500	547,414
Year-Quarter FE	YES	YES	YES
Pseudo R^2	0.011	0.023	0.022

Panel B. Price impact

	Bank Exposed (1)	AIG Exposed (2)	Hurricane Exposed (3)
Similarity_AC_LowRisk_Exp	0.082**	-0.260***	
	(2.259)	(-22.048)	
Similarity_AC_LowRisk_Unexp	0.012**	-0.051***	0.035***
	(2.481)	(-25.624)	(8.597)
Similarity_AC_HighRisk_Exp	0.052**	0.161***	-0.009
	(2.308)	(25.329)	(-1.295)
Similarity_AC_HighRisk_Unexp	0.020***	0.009***	0.032***
	(4.474)	(5.881)	(9.468)
Avg. Ln(Amount)	-0.570***	0.245***	-0.060***
	(-51.577)	(31.969)	(-3.873)
Avg. Ln(Maturity)	0.184***	0.040***	0.142***
	(13.471)	(7.444)	(13.043)
Avg. Ln(Trades)	0.099***	-0.589***	0.027***
	(8.681)	(-114.052)	(2.673)
Prod_Size	-0.005***	0.012***	-0.029***
	(-2.591)	(20.238)	(-20.870)
Prod_Conc_AC	0.572***	-2.456***	1.380***
	(5.594)	(-22.163)	(9.753)
Constant	9.601***	2.946***	1.582***
	(85.581)	(36.315)	(9.809)
N	20,099	142,845	14,535
Adj. R^2	0.293	0.287	0.059

Table 9: Portfolio Similarity as a Determinant of Common Sales at the Insurer Level

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

Panel A: Average Overall Portfolio Similarity

	Asset class		Issuer	
	All	Large	All	Large
	(1)	(2)	(3)	(4)
Similarity_Avg_AC	0.388***	3.329***		
	(2.64)	(9.05)		
Similarity_Avg_I			13.039***	12.610***
			(34.98)	(15.49)
Size	0.859***	0.682***	1.317***	0.795***
	(116.56)	(9.97)	(78.99)	(11.31)
Large	0.559***		-0.287***	
	(11.17)		(-3.14)	
Life	-0.123**	0.292*	-0.360***	0.112
	(-2.00)	(1.66)	(-4.66)	(0.51)
PC	0.151***	-0.361**	-0.232***	-1.022***
	(3.03)	(-2.13)	(-2.92)	(-4.47)
Conc_AC	0.325***	3.366**		
	(3.06)	(2.57)		
Conc_I			-1.653***	10.594**
			(-3.46)	(2.16)
Year-Quarter FE	YES	YES	YES	YES
N	41,821	1,524	43,478	1,528
Pseudo R^2	0.164	0.108	0.054	0.109

Panel B. Average High and Low Risk Asset Class Portfolio Similarity

	All (1)	Large (2)
Similarity_Avg_AC_LowRisk	0.014	2.071***
	(0.09)	(4.95)
Similarity_Avg_AC_HighRisk	0.975***	2.627***
	(5.88)	(2.97)
Size	0.851***	0.731***
	(102.88)	(10.67)
Large	0.459***	
	(9.09)	
Life	-0.856***	0.172
	(-9.38)	(0.99)
PC	-0.529***	-0.311*
	(-6.60)	(-1.81)
Conc_AC	-0.527***	4.885***
	(-4.79)	(3.26)
Conc_I		
Observations	37,436	1,524
Year-Quarter FE	YES	YES
Pseudo R-squared	0.168	0.108

Table 10: Asset Classes Sold

The table presents the composition of holdings and sales for low asset class and high asset class similarity exposed insurers. Low (high) similarity insurers are those whose average portfolio similarity with all other insurers at the asset class level is below (above) the median for the year. In Panel A, an insurer is bank exposed if its portfolio holdings of financial firms' bonds relative to all corporate bonds are in the top quartile of the sample for the year. Proportional holdings are at the end of 2007 and proportional sales are during 2008, using dollar value held or sold to calculate the proportion respectively. In Panel B, an insurer is AIG exposed if its portfolio similarity with AIG at the issuer level is above the median level of the sample in that year. Proportional holdings are at the end of 2007 and proportional sales are during 2008, using dollar value held or sold to calculate the proportion respectively. In Panel C, an insurer is hurricane exposed if its premiums written in hurricane affected states (Mississippi and Louisiana) relative to all premiums written, are in the top quartile of the sample for the year. Proportional holdings are at the end of 2004 and proportional sales are during 2005, using dollar value held or sold to calculate the proportion respectively. We first calculate the proportion held, proportion sold, and the difference between proportion sold and held for each insurer, and then report the cross-sectional mean. Statistical significance for the t-test of whether the difference in the proportion sold and held is different between low-similarity and high-similarity insurers is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

Panel A. Bank exposed

	Low Similarity_Avg_AC			High Similarity_Avg_AC			Diff High-Low	
	Held	Sold	Sold-Held	Held	Sold	Sold-Held	Sold-Held	
Corporate bonds	0.34	0.26	-0.08	0.28	0.30	0.03	0.11	***
Equity	0.16	0.24	0.08	0.10	0.16	0.05	-0.03	
GSE securities	0.12	0.11	-0.01	0.30	0.21	-0.09	-0.09	***
MBS/ABS	0.11	0.04	-0.07	0.11	0.05	-0.06	0.01	
Municipal bonds	0.17	0.12	-0.05	0.13	0.08	-0.05	0.01	
Mutual funds	0.02	0.08	0.06	0.02	0.05	0.03	-0.03	**
Sovereign bonds	0.01	0.01	0.00	0.00	0.00	0.00	0.00	
US govt securities	0.07	0.14	0.07	0.07	0.16	0.09	0.02	

Panel B. AIG exposed

	Low Similarity_Avg_AC			High Similarity_Avg_AC			Diff High-Low	
	Held	Sold	Sold-Held	Held	Sold	Sold-Held	Sold-Held	
Corporate bonds	0.18	0.18	0.00	0.17	0.23	0.07	0.07	**
Equity	0.18	0.25	0.07	0.10	0.20	0.09	0.02	
GSE securities	0.12	0.10	-0.02	0.46	0.28	-0.18	-0.16	***
MBS/ABS	0.04	0.02	-0.02	0.05	0.03	-0.02	-0.01	
Municipal bonds	0.27	0.19	-0.08	0.13	0.07	-0.06	0.02	
Mutual funds	0.07	0.09	0.03	0.02	0.07	0.05	0.02	
Sovereign bonds	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
US govt securities	0.14	0.17	0.03	0.07	0.13	0.06	0.03	

Panel C. Hurricane exposed

	Low Similarity_Avg_AC			High Similarity_Avg_AC			Diff High-Low	
	Held	Sold	Sold-Held	Held	Sold	Sold-Held	Sold-Held	
Corporate bonds	0.17	0.15	-0.02	0.24	0.26	0.02	0.04	*
Equity	0.24	0.28	0.05	0.14	0.22	0.08	0.03	
GSE securities	0.12	0.11	0.00	0.29	0.19	-0.10	-0.10	***
MBS/ABS	0.04	0.04	0.00	0.08	0.06	-0.02	-0.02	
Municipal bonds	0.29	0.18	-0.11	0.15	0.08	-0.07	0.04	
Mutual funds	0.01	0.03	0.01	0.01	0.03	0.02	0.01	
Sovereign bonds	0.01	0.00	0.00	0.01	0.01	0.00	0.01	
US govt securities	0.13	0.20	0.08	0.09	0.16	0.07	-0.01	