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Interconnectedness in the CDS Market

Mila Getmansky, Giulio Girardi, and Craig Lewis

Concentrated risks in the market for credit default swaps (CDSs) are widely considered to have contributed significantly to the 2007–08 financial crisis. We examine the structure of the CDS market using a network-based approach that allows us to capture the interconnectedness between dealers and nondealers of CDS contracts. We find a high degree of interconnectivity among major market participants. Our work helps assess the stability of the CDS market and the potential contagion among market participants. Our findings are of practical importance because even after central clearing becomes mandatory, counterparty risk will remain a relevant systemic consideration owing to the long-term nature of CDS contracts.

The concentration of transactions and positions in the credit default swap (CDS) market among a select group of large dealers is widely considered to have contributed significantly to the 2007–08 financial crisis. Because of the highly concentrated and interconnected nature of bilateral CDS contracting, the counterparty risk associated with potential defaults of large protection sellers is a possible source of systemic risk. Historically, the decentralized nature of over-the-counter (OTC) derivatives markets has made it difficult for regulators and market participants to obtain reliable information on prices and market exposures. The lack of transparency regarding exposures held by market participants complicates the management of counterparty risk. This lack of transparency was reportedly one of the reasons why, before the recent crisis, certain market participants, such as American International Group (AIG), were able to create large, yet unobservable, exposures (e.g., Markose, Giansante, and Shaghaghi 2012).

To the extent that a counterparty failure of a large CDS market participant can result in sequential counterparty defaults that send shock waves throughout the swap market, the ensuing contagion can become systemically important. The systemic implications of the 2007–08 financial crisis resulted in a coordinated policy response in the United States and abroad. In 2009, the G–20 agreed that standardized OTC derivatives contracts should be traded on exchanges or electronic trading platforms (known as swap execution facilities), cleared through central counterparties (CCPs), and reported to "trade repositories." To coordinate this global response, the Financial Stability Board (FSB) was tasked with monitoring the progress of the implementation of these reforms.

In July 2010, the US Congress passed the Dodd–Frank Wall Street Reform and Consumer Protection Act (Dodd–Frank), signed into law by President Obama on 21 July. Dodd–Frank envisioned a set of reforms that would, among other things, "promote the financial stability of the United States by improving accountability and transparency in the financial system."[1] In passing Dodd–Frank, Congress identified the OTC derivatives market as a key source of instability;[2] an overarching aim of Title VII of Dodd–Frank was to mitigate the buildup and transmission of systemic risk in the swap market.[3]

Among its requirements, Title VII mandates the central clearing of certain contracts that, in the aggregate, are deemed to have the potential to create systemic risk. Central clearing is a market practice that may result in significant systemic risk mitigation. Its function is to transfer counterparty risk previously borne by each party to the swap transaction

Mila Getmansky is associate professor of finance at the Isenberg School of Management, University of Massachusetts, Amherst. Giulio Girardi is a financial economist at the US Securities and Exchange Commission, Washington, DC. Craig Lewis is the Madison S. Wigginton Professor of Finance at the Owen Graduate School of Management, Vanderbilt University, and professor of law at Vanderbilt University Law School, Nashville, Tennessee.

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to CCPs. CCPs are designed to reduce the likelihood that the default of a large swap market participant will result in sequential counterparty defaults and to ameliorate systemic risk transmission throughout the swap market.[4] The effectiveness of CCPs is predicated on the requirement that clearing members must post capital and collect margin so that defaults by either counterparties or clearing members can be absorbed. CCPs are considered an effective risk-sharing mechanism that mitigates counterparty risk without necessarily eliminating it.

Many researchers have studied the risks in the OTC markets for CDSs.[5] Some have argued that Title VII reforms may reallocate systemic risk without actually reducing it—if, for example, mandatory clearing for one product precludes more efficient multilateral netting across products (see Duffie and Zhu 2011). Acharya, Shachar, and Subrahmanyam (2010) offer a good overview of the Dodd–Frank Act and CDS clearing requirements.

Despite pending regulatory requirements that mandate central clearing, the majority of single-name CDS transactions remain bilateral trades that are not centrally cleared. Practitioners will continue to need a thorough understanding of how counterparty risk is concentrated among the major security-based swap dealers, for a number of reasons.

First, many of the rules under Title VII of Dodd–Frank have yet to be finalized by the US Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC). Until key components of Title VII are adopted, the decision to centrally clear a trade will remain a voluntary decision that must be agreed to by both parties before the trade is assigned to a CCP. Thus, the market will continue to function in its current state despite regulator encouragement to centrally clear eligible CDS transactions.

Second, not all reference entities—the underlying legal entity on which the CDS is based—are currently eligible for central clearing. Dodd–Frank granted the SEC the authority to determine which contracts are eligible for central clearing (Porter 2015). In making this determination, the SEC should consider a number of factors: (1) sufficient activity, trading liquidity, and adequate pricing data; (2) a well-functioning infrastructure to support clearing; (3) the opportunity for systemic risk mitigation; (4) the impact on competition; and (5) the opportunity to resolve failures of the clearinghouse or clearing members with reasonable legal certainty. Although the SEC is expected to require more reference entities to be centrally cleared, Porter (2015) reported that as of 31 December 2013, only 21% of all single-name reference entities were eligible for clearing (161 of 840 North American single-name reference entities and 121 of 493 European single-name reference entities).[6]

Third, mandatory central clearing will not necessarily eliminate bilateral exposure. Nonstandard contracts are not centrally cleared, and mandatory clearing can be avoided by designing nonstandard contracts for eligible reference entities. The International Swaps and Derivatives Association (ISDA) has developed standard North American corporate (SNAC) documentation for US single-name reference entities that requires standard contracts to have standard coupon rates of either 100 or 500 bps and maturities of 10 years or less. In addition, restructuring cannot be included as a credit event. The extent to which initial cost efficiencies will push CDS trading toward nonstandard contracts has important implications for practitioners, particularly if unwinding these positions is relatively expensive.

A fourth, compelling reason why our study is especially useful to practitioners is that CDS transactions create long-term exposures that will persist, even after central clearing becomes mandatory. CDS transactions obligate dealers to enter into long-term contracts that expose them to significant counterparty risk over the life of each contract. Although economic risk can be reduced by taking offsetting positions, transacting with counterparties to which a dealer has direct exposure is the only way to reduce bilateral exposure. This point is relevant because even if mandatory central clearing were implemented immediately, dealers would continue to have significant counterparty exposure, which would persist until all existing contracts were terminated or had matured. In this context, an important component of monitoring systemic risk is understanding dealers' gross notional exposures vis-à-vis one another and continuing to track bilateral exposures until positions become sufficiently small.

All these reasons explain why an analysis of the interconnectedness in the CDS market is relevant to practitioners—even though Dodd–Frank mandates central clearing. Understanding counterparty concentration, particularly among systemically important financial institutions, is critical because it can create stress on the financial system in the unlikely event of a failure by a large CDS dealer.

In our study, we sought to better understand the structure of the CDS market, looking specifically at its topology (i.e., the mapping of the links between dealers involved in CDS transactions). To do so, we used data from the Trade Information Warehouse (TIW) of the Depository Trust & Clearing Corporation (DTCC), which holds records on approximately 98% of all global credit derivatives transactions by notional amount. Given the breadth of coverage, we were able to obtain a reasonably complete picture of interdealer transactions and positions.[7] The database did not provide information on transactions that fell outside the ambit of US regulators—that is, transactions between two foreign counterparties on a foreign reference entity.[8]

To understand the structure—and conditions for stability and fragility—of the CDS market, we mapped the network of connections between dealers and nondealers. Network-based approaches have been used successfully to study fragility and systemic risk in various markets.[9] These approaches allow for the study of market structure by capturing bilateral connections and evaluating their relative magnitude and by identifying important players—all as a way to understand potential systemic risk. A network approach is useful in studying the dynamics of contagion—that is, how the failure of one financial institution can cause other financial institutions to fail.[10]

Discussion of findings. We studied the structure of the CDS market using explicit connections based on the total number of CDS transactions, the notional value of CDS transactions, and network diagrams. Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000) introduced some of the first formal models of financial contagion. To investigate the fragility of the system, we estimated several network measures for the system between dealers. We report a set of statistics that characterize the CDS market, the degree of counterparty concentration, the size of different contracts, and the underlying contractual features. Our approach considers the size, interconnectedness, and complexity of individual dealers and nondealers and their interrelationships, allowing for the assessment of potential systemic vulnerabilities in the CDS market. We found a high degree of interconnectivity among major market participants. Our findings are relevant in assessing the degree of potential contagion because risk is transmitted across market participants and affects the stability of the system.

One of the unique aspects of our study is that it covers a period after the Volcker rule was proposed but before its formal adoption.[11] The Volcker rule prohibits large bank holding companies from engaging in proprietary trading. Although the rule had yet to be finalized at the end of our sample period, the broad contours of the proposal made it clear that an aggressive interpretation would likely be promulgated—which probably caused banks to preemptively shed many unambiguously proprietary activities.[12]

Consistent with this conjecture, we found that banks may have responded to the anticipated final version of the Volcker rule by reducing both gross notional and net notional exposures in 2012. As banks partially pulled back from CDS markets, nondealers (e.g., hedge funds) responded by increasing their marginal participation levels.

CDS Contracts

A CDS contract is a bilateral agreement that transfers between counterparties the credit exposure on a specific obligation of the reference entity. The protection buyer makes periodic payments to the protection seller in exchange for a positive payoff when a prespecified credit event occurs.[13] When a credit event occurs, the seller of the CDS contract pays the buyer either (1) the notional amount of the CDS contract against delivery of the reference obligation or (2) the difference between the notional amount and the remaining value of the reference obligation as determined in an auction process (depending on whether a physical settlement or a cash settlement is specified).

A party to a CDS contract may exit the contract through termination or novation. In a termination, both contract parties must agree to terminate, possibly for an additional payment that depends on current market conditions. A novation is executed by identifying a market participant willing to assume the obligation of one of the original counterparties at prevailing market prices.

Other contract changes concern "compression" mechanisms, which are designed to cancel redundant contracts when counterparties have taken mutually offsetting positions. For example, if the same counterparties have entered into offsetting positions on contracts with the same economic terms, a compression trade cancels the contracts and creates a new contract with the same net exposure as the original contracts.

Selling protection through a CDS contract replicates a leveraged long position in bonds of the underlying reference entity, exposing protection sellers to risks similar to those of a creditor. In contrast, buying protection through a CDS contract replicates a leveraged short position in bonds of the underlying reference entity, allowing protection buyers to either hedge credit risk they may already be exposed to or effectively take a short position in the credit risk of the underlying reference entity.

Because of their bilateral nature, noncentrally cleared OTC CDS contracts also expose each counterparty to a potential default by the other counterparty. From the perspective of a protection buyer, counterparty risk arises when the protection seller defaults and the buyer loses its protection against default by the reference entity. In contrast, the protection seller carries the risk that the buyer may default, depriving the seller of the expected revenue stream. Depending on the performance of the reference entity at the time of a counterparty default, the CDS contract may be more or less valuable than the original CDS and may thus involve an unanticipated gain or loss. Therefore, both holders of a CDS contract face the risk of loss in two ways: (1) through the performance of the reference entity and (2) through potential counterparty default.

Standardized Contractual Features. ISDA has developed protocols for contract standardization. The original master agreement was established in 1992 and revised in 2002. The primary purpose of these agreements was to create, among other considerations, standards for the netting and collateralization of contracts as well as standards for certain contract specifications, such as contract tenors and credit event triggers.

In 2009, ISDA developed the so-called big bang protocol, which introduced procedures to determine whether a credit event has occurred and specified auction procedures for the pricing of defaulted bonds. ISDA also introduced contract standardization for maturity dates and premium payments (the fixed rates that determine the amount of the periodic payment). For example, CDS premiums were set at 100 or 500 bps for US contracts and at 25, 100, 500, or 1,000 bps for European single-name CDSs. Because prespecified premiums prevent contracts from having zero value on the initiation date, the contract typically requires upfront payments to compensate for the difference between the market premium and the standardized premium.

Finally, a number of issues related to default triggers for European firms caused ISDA to issue the "small bang" protocol in July 2009 to further standardize procedures concerning the determination of credit events. The protocol also applies to the handling of any globally outstanding CDS trades in which the underlying reference entity has engaged in some form of restructuring. The motivations for the convention changes in European contracts are similar to those for the North American convention changes: to facilitate central clearing, gain efficiencies in trade and operational processing, and reduce the gross notional amount outstanding in the market.

Data

We used transaction data for single-name CDSs submitted to the DTCC's Trade Information Warehouse. Established by the DTCC in November 2006, the TIW is the electronic central registry for CDS contracts. We used transaction data, recorded daily, over 1 January 2012 to 31 December 2012—in particular, five snapshots of the positions data: 6 January, 30 March, 29 June, 28 September, and 28 December.

We had access to all TIW data on CDS transactions except for solely foreign transactions. Thus, our sample includes all transactions with at least one of the following: (1) a US reference entity, (2) a US counterparty, (3) a foreign branch of a US counterparty, or (4) a foreign affiliate of a US counterparty. For example, we excluded from the analysis transactions between two non-US counterparties unless they had transacted in CDSs in which the reference entity was a US entity.[14] The total gross notional outstanding at the beginning of our sample was \$11.4 trillion. At the same date (January 2012), the total gross notional globally for single-name CDSs and index CDSs was \$13.8 trillion and \$25.1 trillion, respectively.[15] Therefore, our sample represents about 82.6% of the global single-name CDS market and 45.4% of the total CDS market (including multi-names).

The data identify the counterparties to each transaction. For each individual market participant, the data include a consistent identifier throughout the dataset, its classification by type (dealer versus nondealer), and its domicile.[16] The sample of nondealers includes pension funds, asset managers, hedge funds, banks, and nonfinancial companies (though the dataset does not distinguish between them).[17]

Each transaction record contains the following information: name of the reference entity, trade date, contract maturity date, identities and type (dealer versus nondealer) of the participating counterparties, whether the transaction is cleared,[18] the executed notional amount, market sector to which the reference entity belongs, and other transaction-specific information. Transactions are classified as one of several types. A transaction can be a new trade or a cash settlement of an existing trade, or it can be novated.[19] Contracts can be partially or fully closed out or assigned/novated before maturity.

We applied a number of filters to the data. First, we eliminated both index and product/tranche CDSs, thus leaving single-name corporate and sovereign CDSs to be analyzed.[20] We then deleted trades that had been reassigned within a company and trades in which a counterparty had completed a legal name change but kept contracts that had been partially terminated and assigned. Erroneous records, such as negative notional amounts, were also removed from the data. Finally, we aggregated the names of the counterparties by the highest-level name available. If higher-level information was unavailable, we aggregated by parent name, fund name, or firm name to better understand each counterparty's aggregate involvement in the CDS market.

Methodology

We used several measures of connectedness to map the network of dealers and nondealers. To protect the privacy of market participants, we anonymized the identities of the counterparties by using several masking techniques in reporting our results.

To assess the systemic importance of both dealers and nondealers, we defined several measures of connectedness.

Gross Notional Amounts. This measure has three components:

- *Notional bought:* The gross notional amount bought by each counterparty
- *Notional sold:* The gross notional amount sold by each counterparty
- *Net notional positions outstanding:* The difference between the notional values of all outstanding contracts bought and sold by each counterparty

Number of Contracts. This measure has two components:

- *Number of contracts bought:* The number of CDS contracts bought by each counterparty
- *Number of contracts sold:* The number of CDS contracts sold by each counterparty

Number of Connections. This measure has three components:

- *Number of buy-side connections:* The number of different counterparties from which a specific market participant buys CDS contracts
- *Number of sell-side connections:* The number of different counterparties to which a specific market participant sells CDS contracts
- *Number of buy-side/sell-side connections:* The number of different counterparties that a specific market participant both buys protection from and sells protection to

Average Number of Contracts per Day. This measure has two components:

- *Average number of contracts bought per day:* The average number of CDS contracts bought per day by each counterparty
- *Average number of contracts sold per day:* The average number of CDS contracts sold per day by each counterparty

Concentration Indexes. The Herfindahl–Hirschman Index (HHI) is the most widely used concentration measure (Bikker and Haaf 2002).[21] Therefore, we used the HHI in our analysis.

For each dealer and nondealer i, we calculated the HHI as the sum of squared fractions of CDS contract purchases from other dealers and nondealers j—that is,

$$\text{HHI}_i = \sum_{j=1}^{N} w_{ij}^2,$$

where $i \neq j$, and w_{ij} is the fraction of CDS purchases by a dealer or nondealer from other dealers and nondealers. N is the total number of market participants. By construction, the index ranges from 0 to $1/(N-1)$. It takes the value 1 when a single counterparty buys 100% of its CDS contracts from only one counterparty, and it approaches $1/(N-1)$ when purchases are perfectly diversified across a large number of sellers.[22] This concentration index was inspired by a popular concentration measure originally proposed by Herfindahl (1950) and Hirschman (1964). The result is proportional to the diversification that each counterparty achieves in the long side of its portfolio (i.e., the CDS contracts bought).[23]

We calculated the average HHI by averaging HHI_i across all i types of counterparties:

$$\text{Average HHI} = \frac{\sum_{i=1}^{N} \text{HHI}_i}{N}.$$

The average HHI measures the average diversification that counterparties achieve in the long side of their portfolios.

Dealer Topology. Using network diagrams, we provide information about the overall bilateral exposures between counterparties. The graphical representations of the network are characterized by bilateral relationships across market participants; the results are depicted in **Figure 1**, **Figure 2**, and **Figure 3**. Figure 1 captures the overall gross notional amount traded between counterparties. Figures 2 and 3 capture counterparty topology for all reference entities based on positions data. Both network diagrams use gross outstanding and net outstanding positions.

Results

In describing the results of our empirical analyses, we present the calculations on a highly aggregated basis that incorporates many reference entities and

Figure 1. Dealer Topology for All Reference Entities and All Counterparties Based on 2012 Transaction Data

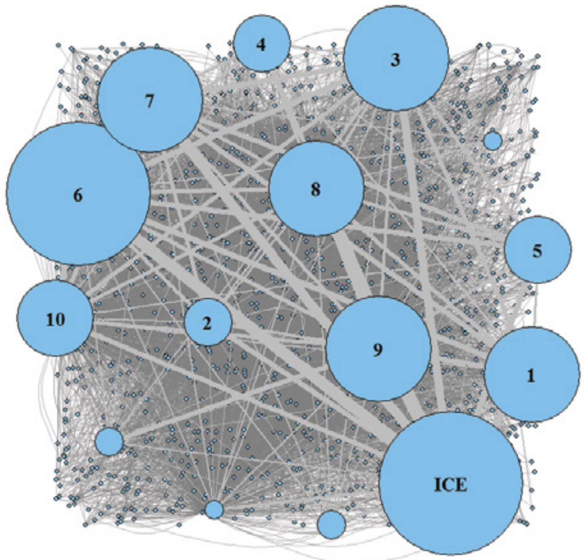
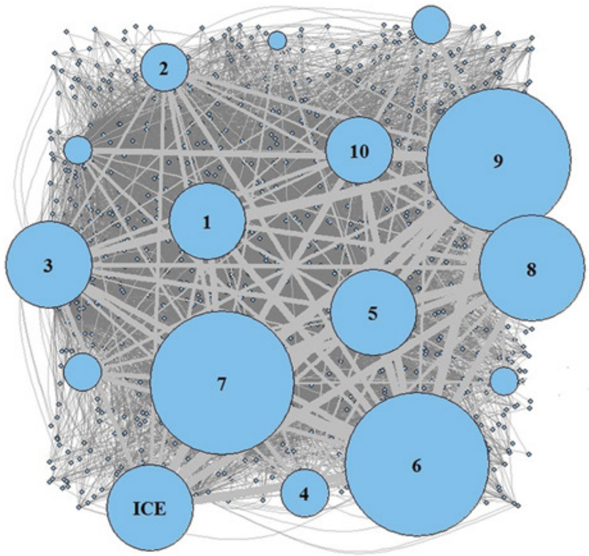
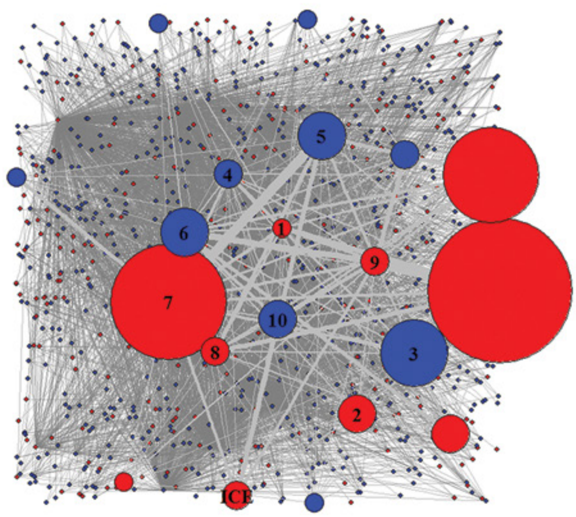


Figure 2. Dealer Topology for All Reference Entities Based on Positions Data, 6 January 2012

A. Gross Outstanding Positions



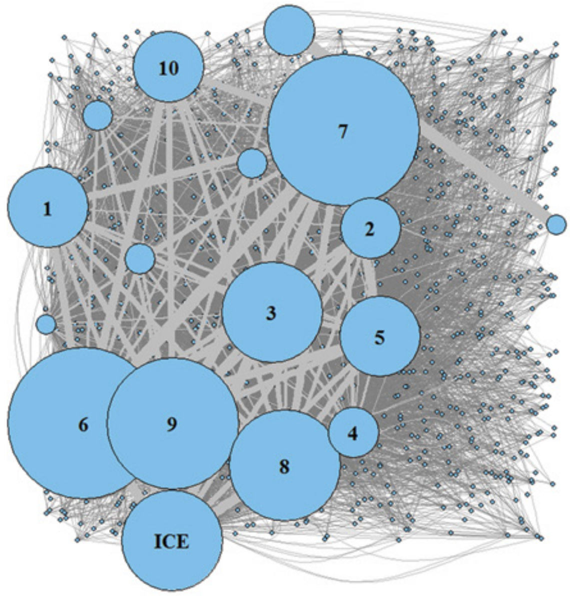
B. Net Outstanding Positions



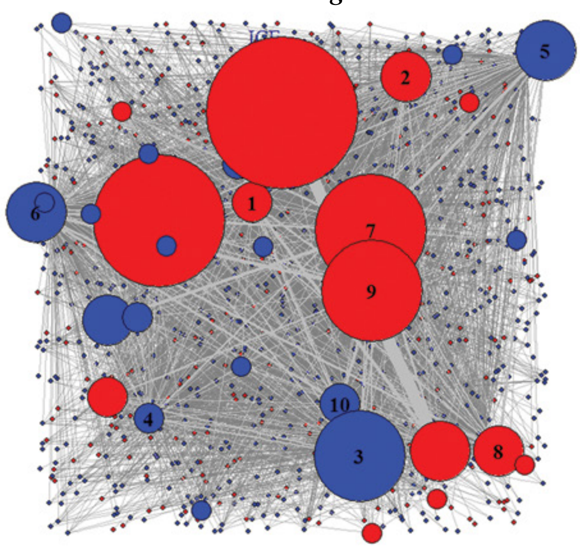
Note: In Panel B, blue represents buyers of CDS contracts, and red represents sellers of CDS contracts.

Figure 3. Dealer Topology for All Reference Entities Based on Positions Data, 28 December 2012

A. Gross Outstanding Positions



B. Net Outstanding Positions



Note: In Panel B, blue represents buyers of CDS contracts, and red represents sellers of CDS contracts.

counterparties. In addition to reporting aggregate statistics, we have reduced the scope of the network connections by providing analyses that focus separately on corporate financial and nonfinancial reference entities for CDS contracts.

Summary Statistics. The gross notional value of all CDS contracts traded in 2012 was $5.07 trillion across 1,758 single-name reference entities.[24] **Table 1** shows that the average daily volume was $15.2 billion,[25] which corresponds to a total of 971,972 trades, or approximately 3,586 contracts traded per trading day. A total of 1,298 market participants bought CDS protection and 1,100 sold protection. Among these market participants, 436 only bought CDS protection, 238 only sold CDS protection, and 862 were on both sides of the market. Among the total number of counterparties that transacted in 2012, 25 were dealers, 2 were CCPs (ICE Clear Credit

Table 1. CDS Market Statistics

	Amount	Number
Notional amount and number of contracts traded		
Total gross notional traded (millions)	$5,070,201	
Average daily volume (millions)	$15,226	
Total number of contracts		971,972
Reference entities		1,758
Number of counterparties by buy side/sell side		
Number of counterparties that buy protection		1,298
Number of counterparties that sell protection		1,100
Number of counterparties that only buy protection		436
Number of counterparties that only sell protection		238
Number of counterparties that buy and sell protection		862
Number of counterparties by type		
Total number of counterparties that transact		1,536
Total number of dealer counterparties that transact		25
Total number of CCPs that transact		2
Total number of nondealer counterparties that transact		1,509

Note: We obtained aggregate market statistics for single-name CDS transactions in 2012 from the DTCC Trade Information Warehouse.

and ICE Clear Europe), and the remaining 1,509 were nondealers.

Table 2 reports the number of unique counterparties for various reference entities. It provides a sense of the type of protection demanded by market participants and how widely the associated counterparty risk is distributed. Table 2 shows that almost all the top 20 reference entities are either sovereigns or financial institutions. The reference entity attracting the most interest is the Kingdom of Spain, with 338 counterparties. The second-most-popular reference entity is the French Republic, with 328 counterparties.

During the eurozone crisis of 2011, CDS contracts written on the sovereign debt of Spain, Italy, and Greece were actively traded as investors sought protection against sovereign defaults. Although Portugal, another country on the European periphery, had similar solvency problems, its sovereign debt was never actively traded. As the eurozone crisis extended into 2012, CDSs written on the sovereign debt of Spain and Italy were among the most actively traded contracts. In contrast, Greek CDS contracts cannot be found in Table 2 because ISDA determined that a Greek restructuring was a credit event, which triggered default payments to protection buyers.

The number of counterparties is a function of demand, availability, and diversification of counterparty risk for various reference entities. For those reference entities outside the top 20, the number of counterparties declines rapidly. Table 2 shows that the average number of counterparties for reference entities in activity bins sorted on the number of counterparties per reference entity—21–100, 101–500, and 501–1,758—drops monotonically from 94 to 49 to 12.

Table 3 provides a more granular look at the size of the market for CDS contracts. It reports the number of contracts traded and their gross notional amounts by reference entity type and market sector. In 2012, corporate CDS contracts represented 84.39% of all contracts traded and 71.07% of the total gross notional amount. Sovereign CDS contracts and "others" made up the remainder. Financials represented the largest portion of corporate contracts traded, accounting for 20.39% of the total number of contracts and 21.20% of the total gross notional amount of CDSs traded. Many of the actively traded reference entities were large bank holding companies, such as Bank of America, Morgan Stanley, and Goldman Sachs. Given the concerns about systemic risk in the aftermath of the financial crisis, investors continued to seek protection against bank failures.

Trading Activity. Because the data identified buyers and sellers, we were able to calculate the total number of contracts bought and sold by different counterparties. We separated counterparties into dealers, nondealers, and those that were centrally cleared. **Table 4** tabulates the number of contracts traded in 2012 by various buyers and sellers, aggregated across size tiers.[26] Dealers represented the majority of buyers and sellers by both number of contracts and gross notional amount. For example, the top 10 buyers and sellers of CDSs in 2012 were all dealers.

Table 2. Number of Unique Counterparties for Various Reference Entities

Reference Entity	Number
Kingdom of Spain	338
French Republic	328
Republic of Italy	266
Federative Republic of Brazil	243
Federal Republic of Germany	220
Bank of America Corporation	173
Morgan Stanley	171
Goldman Sachs Group, Inc.	166
Japan	160
Russian Federation	160
United Mexican States	159
Republic of Turkey	158
JP Morgan Chase & Co.	157
People's Republic of China	157
Citigroup Inc.	154
Republic of Korea	153
Hewlett-Packard Company	152
J.C. Penney Company, Inc.	149
Safeway Inc.	148
Chesapeake Energy Corporation	147
Average (top 21–100 entities)	94
Average (top 101–500 entities)	49
Average (top 501–1,758 entities)	12

Notes: This table reports the number of unique counterparties for the 1,758 different reference entities, sorted on the basis of the number of counterparties per reference entity. It shows the number of unique counterparties for the top 20 reference entities and the average number of counterparties for three activity bins (21–100, 101–500, and 501–1,758) for contracts traded in 2012. Activity bins are sorted on the number of unique counterparties per reference entity.

Table 3. Number of Contracts and Gross Notional Amounts by Reference Entity Type and Market Sector

	Number of Contracts		Gross Notional Amount	
Grouping	Amount (no.)	Total (%)	Amount ($ millions)	Total (%)
Corporate	820,240	84.39	3,603,258	71.07
Financials	198,207	20.39	1,075,192	21.20
Consumer services	151,961	15.63	582,341	11.49
Consumer goods	121,059	12.45	515,917	10.18
Industrials	80,199	8.25	331,927	6.55
Basic materials	63,953	6.58	256,521	5.06
Technology	44,083	4.54	148,507	2.93
Telecommunications services	48,289	4.97	223,621	4.41
Utilities	43,508	4.48	184,928	3.65
Energy	43,395	4.46	173,565	3.42
Health care	25,458	2.62	109,743	2.16
Unknown	128	0.01	995	0.02
Sovereign (government)	144,816	14.90	1,434,878	28.30
Others	1,386	0.14	5,407	0.11
Unknown	5,530	0.57	26,659	0.53
Grand total	971,972	100.00	5,070,201	100.00

Note: This table reports the number and gross notional amounts of contracts traded in 2012 for different reference entity types and market sectors.

Table 4. Number of Contracts and Gross Notional Traded by Counterparty Grouping

	Buy Side				Sell Side			
	Number of Contracts		Gross Notional Traded		Number of Contracts		Gross Notional Traded	
Grouping	Amount (no.)	Total (%)	Amount ($ millions)	Total (%)	Amount (no.)	Total (%)	Amount ($ millions)	Total (%)
Tier 1 (top 5)	405,656	41.74	2,454,094	42.67	443,433	45.62	2,665,863	46.35
Tier 2 (6–10)	258,424	26.59	1,477,992	25.70	271,107	27.89	1,580,215	27.48
Tier 3 (11–15)	63,499	6.53	390,372	6.79	71,167	7.32	380,197	6.61
Tier 4 (16–20)	24,285	2.50	108,113	1.88	23,578	2.43	124,620	2.17
Other dealers	10,481	1.08	35,412	0.62	3,502	0.36	29,969	0.52
Other nondealers	111,172	11.44	605,456	10.53	60,494	6.22	288,099	5.01
Central clearing	98,455	10.13	679,607	11.82	98,691	10.15	682,082	11.86
Grand total	971,972	100.00	5,751,046	100.00	971,972	100.00	5,751,045	100.00

Notes: This table reports transaction activity for single-name CDS contracts by counterparty grouping for 2012. The top 20 counterparties for both buy and sell sides are grouped on the basis of the size of the characteristic (buy-/sell-side number of contracts or gross notional traded). The table also reports statistics for the remaining dealer and nondealer counterparties and for all contracts that are centrally cleared.

Consistent with previous studies (e.g., ECB 2009; Peltonen, Scheicher, and Vuillemey 2013), we found that the five largest buyers, by number of contracts, were the counterparties for 41.74% of all contracts bought in 2012. Cumulatively, the top 10 and the top 20 buyers accounted for 68.33% (41.74 + 26.59) and 77.36% (68.33 + 6.53 + 2.50), respectively, of all market activity in 2012. Under our counterparty classifications, the top 10 buyers of CDS contracts were all dealers. A number of nondealers were among the top 11–20 buyers (tiers 3 and 4). Note that 10.13% of all transactions were cleared through the available clearinghouses (ICE Clear Credit and ICE Clear Europe).

Selling activity was more concentrated in 2012. The top 10 sellers of CDS protection transacted in 73.51% of all contracts traded in 2012, whereas the top 20 sellers captured 83.26% of all contracts sold. Similar to buyers, the top 10 sellers were all dealers, but there were some nondealers in the top 11–20 sellers (tiers 3 and 4), as was also the case for buyers. The disproportionate amount of selling relative to buying by the top 10 dealers suggests that they tend to be net sellers of protection. Not surprisingly, the fraction of contracts sold that were centrally cleared is comparable to the fraction of contracts that were bought and submitted for clearing.[27]

Table 4 also aggregates the top buyers and sellers by gross notional amount of CDS contracts traded in 2012. The qualitative implications are similar to those concerning the number of contracts. For example, the top 20 buyers of CDS protection purchased 77.04% of the notional amount of all contracts in 2012, whereas the top 20 sellers of CDS protection sold 82.61% of the notional amount of all contracts.

Next, we tabulated the average number of contracts traded per counterparty. **Table 5** reports the average daily number of contracts bought or sold by counterparty grouping in 2012. We grouped counterparties into tiers, with tier 1 representing the top five counterparties sorted on the average number of contracts bought or sold per day and tier 7 representing counterparties with the fewest number of

Table 5. Average Daily Number of Contracts Bought or Sold by Counterparty Grouping

Top Buyers	Average Daily Number of Contracts	Top Sellers	Average Daily Number of Contracts
Tier 1 (top 5)	244.73	Tier 1 (top 5)	266.33
Tier 2 (6–10)	176.14	Tier 2 (6–10)	184.49
Tier 3 (11–15)	64.52	Tier 3 (11–15)	67.19
Tier 4 (16–20)	20.23	Tier 4 (16–20)	22.93
Tier 5 (21–100)	3.32	Tier 5 (21–100)	1.92
Tier 6 (101–500)	0.27	Tier 6 (101–500)	0.14
Tier 7 (501–1,298)	0.02	Tier 7 (501–1,100)	0.01

Notes: This table reports the average daily number of contracts traded in 2012. The top buyers and sellers are sorted into seven tiers on the basis of the average number of contracts traded per day. The first four tiers contain the 20 most active counterparties, tiers 5 and 6 contain the next 80 and 400 most active counterparties, and tier 7 includes all other counterparties (501–1,298 for buyers and 501–1,100 for sellers).

daily transactions. Table 5 demonstrates that daily buying and selling is also concentrated among the top 20 counterparties. In 2012, the top buyers (sellers) transacted, on average, 244.73 (266.33) contracts a day. Activity levels drop for counterparties below tier 4; for these tiers, the majority of counterparties bought or sold less than one contract a day. These results indicate that much of the activity is concentrated among a select number of counterparties. Moreover, the number of trades suggests that there is less liquidity in these markets than is typically found in equity markets. The relatively large size of individual trades, coupled with low transaction volume, is more consistent with trading levels in fixed-income markets, which remain over the counter for the most part.

Trading among Counterparties and Network Connectivity. We then characterized, on the basis of trading activity, the network connections across all counterparties. **Table 6** reports the number of connections—that is, the number of counterparties with which each entity (dealer, nondealer, or ICE Clear Credit/ICE Clear Europe) traded CDS contracts. In 2012, there were 8,196 unique connections between 1,536 counterparties.

In describing network connectivity, the concept of density is frequently used to characterize the nature of the connections. Density is defined as the number of actual connections relative to the number of possible connections. The network of CDS connections has a low density (8,196/1,178,880 = 0.0070) because the number of actual links is small compared with the number of all possible links. In 2012, the vast majority of counterparties had no direct bilateral links. The top 5 counterparties had a total of 2,283 buy-side connections with distinct counterparties, whereas the top 20 counterparties had 3,923 buy-side connections. Given the nature of this market, this result makes intuitive sense because the top 5 counterparties are always dealers. We found similar results for both the sell-side and the buy-side/sell-side unique connections.

Table 6 indicates that although the vast majority of trading activity was funneled through the top 10 dealers (Table 4), the top 10 dealers engaged with a large number of nondealer counterparties. The simplest way to illustrate this point is to compute the average number of connections per counterparty from Table 6. Even though the majority of CDS transactions were conducted by dealers only (Table 4), the number of unique counterparties that each dealer engaged with is very high. On average, each of the top 10 dealers had 347.6 buy-side connections [(2,283 + 1,193)/10] and 421.8 sell-side connections [(2,803 + 1,415)/10]. This finding implies a high degree of interconnectivity and a tendency to sell to more counterparties than are bought from. In contrast, "other nondealers" had an average number of buy-side and sell-side connections of 2.8 and 2.3, respectively, which suggests a low degree of interconnectivity and a tendency to buy from more counterparties than are sold to.

Consistent with Peltonen et al. (2013), the picture that emerges from Table 6 is one of a network in which only a small number of all possible links actually exist because the vast majority of the connections are between core counterparties (top 10 dealers) and nondealers. In terms of stability and contagion, this finding suggests that the CDS network may be relatively robust to the disappearance of a random node but could be vulnerable if a few highly connected dealers failed.

We further investigated the bilateral relationships between market participants. **Table 7** shows the aggregate gross notional amounts of CDS protection

Table 6. Number of Unique Connections by Counterparty Grouping

	Buy-Side Connections		Sell-Side Connections		Buy- and Sell-Side Connections	
Grouping	Amount (no.)	Total (%)	Amount (no.)	Total (%)	Amount (no.)	Total (%)
Tier 1 (top 5)	2,283	27.86	2,803	34.20	1,735	31.99
Tier 2 (6–10)	1,193	14.56	1,415	17.26	855	15.77
Tier 3 (11–15)	311	3.79	339	4.14	207	3.82
Tier 4 (16–20)	136	1.66	114	1.39	126	2.32
Other dealers	58	0.71	50	0.61	49	0.90
Other nondealers	4,186	51.07	3,446	42.04	2432	44.85
Central clearing	29	0.35	29	0.35	19	0.35
Grand total	8,196	100.00	8,196	100.00	5,423	100.00

Notes: This table reports the number of distinct connections by counterparty grouping for 2012. The top 20 counterparties of single-name CDS contracts are grouped into four tiers on the basis of the number of unique connections: (1) exclusively buys protection from the other counterparty (buy-side connections), (2) exclusively sells protection to the other counterparty (sell-side connections), and (3) exclusively buys protection from and sells protection to the other counterparty (buy- and sell-side connections). The table also reports the number of connections for the remaining dealer and nondealer counterparties and for all contracts that are centrally cleared.

Table 7. Aggregate Gross Notional Amounts of CDS Protection Bought and Sold
($ millions, except HHI)

	1	2	3	4	5	6	7	8	9	10	Other Dealers	Nondealers	Centrally Cleared	Total	HHI
1	—	9,907	36,123	16,928	17,412	51,533	43,823	34,462	44,520	13,835	13,954	73,941	57,806	414,244	0.11
2	9,888	—	18,869	5,822	5,338	33,386	32,599	18,990	23,306	8,796	6,329	15,740	44,766	223,828	0.12
3	37,347	20,433	—	22,697	27,214	51,790	43,606	23,871	27,141	36,522	43,618	87,537	67,874	489,650	0.10
4	14,166	6,833	16,673	—	11,709	28,926	23,400	17,989	21,563	8,695	9,694	45,586	36,996	242,231	0.11
5	18,452	6,272	28,965	9,184	—	39,566	41,244	32,950	28,168	8,882	9,083	39,646	47,492	309,906	0.11
6	52,752	34,038	55,911	31,466	44,176	—	54,260	37,627	39,790	53,517	50,814	118,461	100,149	672,962	0.10
7	50,236	28,906	47,510	27,413	41,837	64,353	—	33,151	34,093	35,926	45,925	3,312	79,301	491,962	0.10
8	34,266	21,219	24,831	18,362	28,248	38,285	29,560	—	31,661	30,953	41,937	46,699	76,182	422,202	0.10
9	41,201	20,471	26,615	23,564	26,207	41,946	28,294	30,581	—	24,690	73,411	50,119	57,242	444,340	0.10
10	13,166	10,746	39,103	11,379	9,668	53,866	38,901	29,402	30,324	—	24,012	21,746	50,095	332,408	0.11
Other dealers	17,162	6,133	43,922	8,993	10,694	53,877	47,830	40,388	82,501	26,374	7,743	23,781	64,179	433,578	0.11
Nondealers	79,613	18,574	98,277	38,422	46,005	136,400	5,300	59,341	60,808	28,337	22,316	631	—	594,022	0.13
Centrally cleared	58,851	40,035	71,386	35,925	48,620	105,092	74,771	79,394	62,934	43,997	58,603	—	—	679,607	0.10
Total	427,099	223,567	508,186	250,156	317,125	699,020	463,588	438,146	486,809	320,524	407,438	527,199	682,082	5,750,938	**0.08**
Average															**0.11**

Notes: This table reports the network of buyer bilateral transactions for the top 10 dealers, other dealers, nondealers, and centrally cleared contracts (ICE) across all reference entities in 2012. Each row shows the gross notional amount of CDS purchases by a top 10 dealer, other dealers, nondealers, and ICE from other top 10 dealers, other dealers, nondealers, and ICE. HHI is a concentration index.

that was bought and sold in 2012. It reports notional amounts for the top 10 dealers, other dealers, and nondealers; the amounts that were centrally cleared; and the grand total.[28] The top 10 dealers were those that had traded the largest gross notional amounts in 2012.[29]

To understand the table's content, note that each row reports the aggregate gross notional amounts of CDS protection purchased by one counterparty from others, with the counterparties consisting of the top 10 dealers, other dealers, nondealers, and ICE. Each column reports the aggregate notional amounts of CDS protection sold by that counterparty to other counterparties. For example, the first row of Table 7 reports that Dealer 1 purchased $9.907 billion and $43.823 billion of credit protection from Dealers 2 and 7, respectively.[30] It also shows that $79.613 billion of Dealer 1's CDS protection sales were to accommodate the demand from nondealers.[31] Of the $414.244 billion of gross notional protection purchased by Dealer 1 in 2012, only 14% (57,806/414,244) was centrally cleared (i.e., purchased by ICE).

Table 7 shows that most transactions were between dealers that might have been managing their inventories after entering into initial transactions with nondealers. We also found some evidence of dealer-to-dealer clienteles, which can be seen in Table 7 as a tendency for dealers to direct a greater fraction of trades to specific dealers. None of the top 10 dealers, however, traded exclusively with any particular counterparty. For example, the largest percentage of both buy and sell transactions for a given dealer was 16.2% (53,866/332,408)—the amount of CDSs that Dealer 10 bought from Dealer 6 as a percentage of the total notional amount of its CDS purchases. On the basis of each counterparty's HHI (ranging from 0.10 to 0.12), there is no evidence of a significant concentration of transactions among the top 10 dealers. We obtained qualitatively similar results using the entropy concentration index as an alternative concentration measure. In unreported results, we split the sample into corporate financial and nonfinancial reference entities and, once again, obtained qualitatively similar results.[32]

Because this analysis focused on gross notional amounts, a corresponding analysis of net notional exposure allowed us to differentiate between market participants that were net buyers and net sellers. This approach afforded us a better understanding of how much credit risk is transferred between market participants and the economic exposure related to counterparty risk. For example, Dealer 1 purchased protection for an aggregate gross notional amount of $9.907 billion from Dealer 2 and sold Dealer 2 protection for a gross notional amount of $9.888 billion. Netting these amounts indicates that across all CDS contracts, Dealer 1 was a net protection seller ($9.907 billion – $9.888 billion = $19 million) to Dealer 2. The small size of the net trades relative to the gross amounts suggests that in the aggregate, their trading activity was fairly flat. We then investigated more closely the net outstanding exposures among market participants.

Network Connectivity with Gross and Net Positions. We characterized network connections across all counterparties on the basis of aggregate gross and net notional positions. By incorporating positions data into our analysis, we were able to evaluate whether the network picture changed relative to our transaction-based analysis.

Table 8 reports aggregate gross notional positions for CDS protection bought and sold as of 28 December 2012. It has the same format as Table 7. Each row shows the aggregate gross notional positions that a particular counterparty has purchased from all the other counterparties, and each column reports the aggregate notional positions that each counterparty has sold. For example, the first row shows that Dealer 1 held $610.284 billion of notional credit protection that it purchased from other counterparties. To accumulate this position, Dealer 1 purchased and continued to own $19.562 billion and $89.025 billion of notional protection from Dealers 2 and 7, respectively. It also sold aggregate notional protection to these same counterparties for $17.430 billion and $89.397 billion.

This analysis tracks the historical accumulation of positions and can be used to determine the most active market participants. Because CDS trades are bilateral contracts that remain open until their expiration date, past transaction activity is reflected in gross notional amounts for an extended period even though the economic exposure may already have been unwound. For example, Dealer 7 was a net protection seller, having accumulated $2.428 trillion of open positions ($1.190 trillion protection bought + $1.238 trillion protection sold), with an aggregate net exposure of –$0.48 trillion. In contrast, Dealer 6 was a net protection buyer, with $2.413 trillion of open positions and an aggregate net exposure of $0.25 trillion. The small net notional exposures relative to the size of the open positions suggest that dealers maintain relatively flat books.[33]

Table 9 nets the aggregate gross notional amounts and reports the net notional positions as of 28 December 2012. Rather than focus on the aggregate net exposure of each counterparty category with respect to itself, Table 9 computes the aggregate net exposure of market participants with respect to one another. For example, the first row shows that Dealer 1 was a net protection buyer from Dealer 2 ($19.562 billion – $17.430 billion = $2.132 billion) and a net

Table 8. Aggregate Gross Notional Positions for CDS Protection Bought and Sold, 28 December 2012 ($ millions)

	1	2	3	4	5	6	7	8	9	10	Other Dealers	Nondealers	Centrally Cleared	Total
1	—	19,562	60,133	13,345	32,699	85,153	89,025	60,301	80,369	22,519	67,338	31,732	48,108	610,284
2	17,430	—	34,765	8,476	13,114	61,833	63,593	40,241	48,558	18,123	22,815	10,381	62,337	401,664
3	64,958	39,394	—	38,845	60,913	98,655	83,210	55,813	70,039	53,026	113,524	42,105	66,490	786,972
4	16,460	10,684	33,120	—	19,851	53,366	47,715	37,942	40,757	11,334	22,242	38,759	28,020	360,251
5	36,750	15,048	60,403	19,795	—	94,926	108,848	79,854	87,064	24,280	41,379	36,459	53,804	658,610
6	92,911	62,536	96,645	50,170	94,771	—	143,920	98,193	117,907	101,578	187,275	67,424	105,639	1,218,968
7	89,397	60,477	76,519	45,411	91,046	138,313	—	91,405	111,421	85,717	141,359	133,068	125,980	1,190,113
8	63,730	40,131	53,614	38,802	66,566	87,537	84,222	—	78,230	61,085	140,039	47,491	105,646	867,094
9	75,623	48,511	64,907	39,539	78,078	103,811	109,522	72,623	—	64,424	163,608	81,147	111,940	1,013,733
10	23,611	19,410	52,590	14,881	20,579	91,222	87,048	58,411	74,421	—	48,379	12,443	45,712	548,707
Other dealers	55,371	22,159	97,690	22,583	37,732	169,561	174,627	123,146	189,869	39,708	68,326	203,751	36,485	1,241,011
Nondealers	40,159	18,772	43,573	28,982	45,520	104,486	132,414	57,393	49,661	20,511	144,283	5,813	—	691,569
Centrally cleared	47,796	65,734	73,888	27,533	71,532	105,220	114,119	110,973	108,192	31,004	36,291	—	—	792,283
Total	624,195	422,418	747,849	348,363	632,403	1,194,083	1,238,262	886,294	1,056,488	533,309	1,196,859	710,573	790,162	10,381,258

Notes: This table reports the network of bilateral gross outstanding positions across all reference entities as of 28 December 2012. Each row shows the gross notional amount of CDS outstanding positions by a top 10 dealer, other dealers, nondealers, and centrally cleared contracts (ICE) with respect to other top 10 dealers, other dealers, nondealers, and ICE.

Table 9. Net Notional Positions, 28 December 2012
($ millions)

	1	2	3	4	5	6	7	8	9	10	Other Dealers	Nondealers	Centrally Cleared	Total
1	—	2,132	(4,825)	(3,114)	(4,052)	(7,757)	(372)	(3,428)	4,746	(1,092)	11,967	(8,428)	313	(13,911)
2	(2,132)	—	(4,629)	(2,208)	(1,933)	(703)	3,116	110	47	(1,288)	656	(8,391)	(3,398)	(20,753)
3	4,825	4,629	—	5,725	510	2,009	6,690	2,199	5,132	436	15,834	(1,468)	(7,398)	39,123
4	3,114	2,208	(5,725)	—	56	3,197	2,303	(860)	1,219	(3,547)	(341)	9,777	487	11,888
5	4,052	1,933	(510)	(56)	—	155	17,802	13,287	8,986	3,701	3,647	(9,062)	(17,728)	26,207
6	7,757	703	(2,009)	(3,197)	(155)	—	5,607	10,657	14,095	10,356	17,713	(37,062)	419	24,885
7	372	(3,116)	(6,690)	(2,303)	(17,802)	(5,607)	—	7,183	1,899	(1,330)	(33,268)	654	11,861	(48,149)
8	3,428	(110)	(2,199)	860	(13,287)	(10,657)	(7,183)	—	5,607	2,675	16,893	(9,903)	(5,326)	(19,200)
9	(4,746)	(47)	(5,132)	(1,219)	(8,986)	(14,095)	(1,899)	(5,607)	—	(9,997)	(26,261)	31,486	3,748	(42,756)
10	1,092	1,288	(436)	3,547	(3,701)	(10,356)	1,330	(2,675)	9,997	—	8,671	(8,068)	14,708	15,397
Other dealers	(11,967)	(656)	(15,834)	341	(3,647)	(17,713)	33,268	(16,893)	26,261	(8,671)	—	59,468	194	44,152
Nondealers	8,428	8,391	1,468	(9,777)	9,062	37,062	(654)	9,903	(31,486)	8,068	(59,468)	—	—	(19,004)
Centrally cleared	(313)	3,398	7,398	(487)	17,728	(419)	(11,861)	5,326	(3,748)	(14,708)	(194)	—	—	2,120
Total	13,911	20,753	(39,123)	(11,888)	(26,207)	(24,885)	48,149	19,200	42,756	(15,397)	(44,152)	19,004	(2,120)	163,773

Notes: This table reports the network of bilateral net outstanding positions across all reference entities as of 28 December 2012. Each row shows the gross notional amount of CDS outstanding positions by a top 10 dealer, other dealers, nondealers, and centrally cleared contracts (ICE) with respect to other top 10 dealers, other dealers, nondealers, and ICE.

protection seller to Dealer 7 ($89.025 billion – $89.397 billion = –$372 million). This finding indicates that even though Dealer 1 traded more often with Dealer 7 ($89.025 billion + $89.397 billion = $178.422 billion) than with Dealer 2 ($19.562 billion + $17.430 billion = $36.992 billion), Dealer 1 actually had less economic exposure to Dealer 7. Thus, it is important to emphasize that gross and net positions provide differing views about counterparty risk exposures and the amount of inventory on hand.

Table 10 converts the net dollar positions into proportions based on aggregate gross notional exposure. For example, the nondealer net positions outstanding as a percentage of gross positions outstanding is only –1.4%. Moreover, the largest percentage of net to gross positions is only 2.5%. The results suggest that market participants tend to adjust net exposures dynamically.

Table 11 reports buy-side gross and net notional positions and the net notional as a percentage of total gross positions for five snapshots of the 2012 database: 6 January, 30 March, 29 June, 28 September, and 28 December. The change in net positions over time reveals an interesting trend during our sample period. Although dealers (both top 10 dealers and other dealers) began the year as net protection sellers, they became net protection buyers by year-end ($16.883 billion). Nondealers (e.g., hedge funds, asset managers, and insurers) served as counterparties to these trades and became net protection sellers (–$19.004 billion).[34] Table 11 also shows that both dealers and nondealers decreased their net exposure to CDS contracts. Because more contracts were being centrally cleared by year-end, dealers also had reduced counterparty risk.

Dodd–Frank regulations and SIFI (systemically important financial institution) designations for many banks may have been one of the causes of a general decrease in risks taken by CDS dealers operating as part of a bank holding company. The biggest change seems to have occurred for other dealers and nondealers, which, almost in parallel and with similar magnitude, decreased and increased their net selling, respectively.[35]

Graphical Depiction of Network Connectivity. Figure 1 captures the overall gross notional amounts traded between counterparties as identified in Table 7. It depicts the connections for the top 10 dealers, other dealers, nondealers, and ICE. The thickness of connections between two counterparties is indicative of the notional amount of CDS contracts traded. Thicker lines indicate larger notional amounts of CDS contracts traded between two counterparties. The size of the nodes reflects the overall amount traded by the particular counterparty. Similar to the results reported in Table 7, most of the transactions were conducted by top 10 dealers and most bilateral transactions were between these top 10 counterparties. Note that many dealers chose to clear their transactions through ICE, although most of their transactions still occurred over the counter.

Figure 2 depicts counterparty topology for all reference entities on the basis of positions data at the beginning of 2012 (6 January 2012). Both network diagrams reflect gross outstanding positions and net outstanding positions. Regarding gross outstanding positions, the top 10 dealers clearly accumulated and held the largest number of gross outstanding positions. Specifically, nodes 6, 7, 8, and 9 are the largest in the network, with ICE representing a significant portion of total gross outstanding positions. Interestingly, the picture for net (buy minus sell) positions is very different. Most of the top 10 dealers (except Dealer 7) had relatively small net exposures to CDS contracts. Instead, several nondealers and other dealers emerged as major net sellers of such contracts—among the top 10 net sellers, 2 were nondealers (ranked 3rd and 8th), 3 were other dealers (ranked 1st, 4th, and 10th), and 5 were top 10 dealers.

Figure 3 is analogous to Figure 2. It provides the same network diagrams as of 28 December 2012. The main takeaway corroborates our findings that dealers lowered their economic exposure and some nondealers emerged as large net protection sellers. Indeed, the two largest net sellers of CDS protection were nondealers. A few top 10 dealers continued to be large net sellers, whereas other dealers noticeably reduced their exposures (ranked 5th, 8th, and 10th among the largest protection sellers).

Conclusion

In this article, we presented the results of our study of the OTC market for credit default swaps. Using network methodology, we mapped the network of connections between dealers and nondealers of CDS contracts. We found that the network of dealers is highly concentrated for different kinds of CDS contracts. More than 70% of all CDS contracts are bought or sold by the top 10 counterparties, all of which are dealers. This finding suggests that there is significant activity among dealers that probably arises from managing net risk exposures. In addition to dealer activity, a number of large nondealers transact at sufficient levels to put them among the top 20 counterparties (based on total CDS contract volume). Overall, the interconnectedness of the CDS market is largely attributable to end users that transact with a relatively small number of dealers, who then manage net exposures by trading among themselves. The picture that emerges is one of a network that is relatively robust to the disappearance of a random node but potentially vulnerable if

Table 10. Gross Notional Amount of CDS Outstanding Positions as a Percentage of Gross Outstanding Positions, 28 December 2012
(all numbers in percentages)

	1	2	3	4	5	6	7	8	9	10	Other Dealers	Nondealers	Centrally Cleared	Total
1	—	5.8	–3.9	–10.4	–5.8	–4.4	–0.2	–2.8	3.0	–2.4	9.8	–11.7	0.3	–1.1
2	–5.8	—	–6.2	–11.5	–6.9	–0.6	2.5	0.1	0.0	–3.4	1.5	–28.8	–2.7	–2.5
3	3.9	6.2	—	8.0	0.4	1.0	4.2	2.0	3.8	0.4	7.5	–1.7	–5.3	2.5
4	10.4	11.5	–8.0	—	0.1	3.1	2.5	–1.1	1.5	–13.5	–0.8	14.4	0.9	1.7
5	5.8	6.9	–0.4	–0.1	—	0.1	8.9	9.1	5.4	8.3	4.6	–11.1	–14.1	2.0
6	4.4	0.6	–1.0	–3.1	–0.1	—	2.0	5.7	6.4	5.4	5.0	–21.6	0.2	1.0
7	0.2	–2.5	–4.2	–2.5	–8.9	–2.0	—	4.1	0.9	–0.8	–10.5	0.2	4.9	–2.0
8	2.8	–0.1	–2.0	1.1	–9.1	–5.7	–4.1	—	3.7	2.2	6.4	–9.4	–2.5	–1.1
9	–3.0	0.0	–3.8	–1.5	–5.4	–6.4	–0.9	–3.7	—	–7.2	–7.4	24.1	1.7	–2.1
10	2.4	3.4	–0.4	13.5	–8.3	–5.4	0.8	–2.2	7.2	—	9.8	–24.5	19.2	1.4
Other dealers	–9.8	–1.5	–7.5	0.8	–4.6	–5.0	10.5	–6.4	7.4	–9.8	0.0	17.1	0.3	1.8
Nondealers	11.7	28.8	1.7	–14.4	11.1	21.6	–0.2	9.4	–24.1	24.5	–17.1	0.0	—	–1.4
Centrally cleared	–0.3	2.7	5.3	–0.9	14.1	–0.2	–4.9	2.5	–1.7	–19.2	–0.3	—	—	0.1
Total	1.1	2.5	–2.5	–1.7	–2.0	–1.0	2.0	1.1	2.1	–1.4	–1.8	1.4	–0.1	

Notes: This table reports the network of bilateral net outstanding positions as a percentage of gross outstanding positions across all reference entities as of 28 December 2012. Each row shows the gross notional amount of CDS outstanding positions as a percentage of gross outstanding positions by a top 10 dealer, other dealers, nondealers, and centrally cleared contracts (ICE) with respect to other top 10 dealers, other dealers, nondealers, and ICE.

Table 11. Buy-Side Gross and Net Notional Positions for Five Snapshots of the 2012 Database

	Buy-Side Gross Notional Positions ($ millions)					Buy-Side Net Notional Positions ($ millions)					Net Notional as Percentage of Total Gross Positions				
	06 Jan	30 Mar	29 Jun	28 Sep	28 Dec	06 Jan	30 Mar	29 Jun	28 Sep	28 Dec	06 Jan	30 Mar	29 Jun	28 Sep	28 Dec
1	691,966	686,108	642,258	628,145	610,284	(12,498)	(14,082)	(21,733)	(17,668)	(13,911)	–0.9%	–1.0%	–1.7%	–1.4%	–1.1%
2	403,782	401,521	404,273	396,647	401,664	(25,481)	(27,270)	(25,273)	(23,359)	(20,753)	–3.1	–3.3	–3.0	–2.9	–2.5
3	812,802	840,858	828,053	820,184	786,972	47,623	49,549	55,896	52,904	39,123	3.0	3.0	3.5	3.3	2.5
4	404,654	406,929	395,084	377,651	360,251	18,636	14,806	11,962	10,437	11,888	2.4	1.9	1.5	1.4	1.7
5	810,031	792,385	731,989	699,803	658,610	30,613	31,058	22,272	19,240	26,207	1.9	2.0	1.5	1.4	2.0
6	1,341,547	1,341,669	1,287,077	1,257,631	1,218,968	34,938	36,872	31,372	24,074	24,885	1.3	1.4	1.2	1.0	1.0
7	1,312,836	1,325,821	1,257,710	1,242,193	1,190,113	(86,492)	(75,092)	(55,264)	(46,910)	(48,149)	–3.2	–2.8	–2.1	–1.9	–2.0
8	954,932	956,204	906,787	899,242	867,094	(15,401)	(14,262)	(17,850)	(15,359)	(19,200)	–0.8	–0.7	–1.0	–0.8	–1.1
9	1,270,818	1,238,093	1,112,660	1,084,680	1,013,733	(21,651)	(29,681)	(35,706)	(46,312)	(42,756)	–0.8	–1.2	–1.6	–2.1	–2.1
10	643,641	656,234	638,415	601,352	548,707	30,151	27,936	33,898	38,316	15,397	2.4	2.2	2.7	3.3	1.4
Other dealers	1,393,007	1,509,916	1,453,769	1,402,390	1,241,011	(126,498)	(82,823)	(61,075)	(48,095)	44,152	–4.3	–2.7	–2.1	–1.7	1.8
Nondealers	647,177	891,833	791,527	768,098	691,569	141,556	98,580	72,525	54,826	(19,004)	12.3	5.9	4.8	3.7	–1.4
Centrally cleared	771,088	790,073	793,882	768,754	792,283	(15,495)	(15,590)	(11,026)	(2,094)	2,120	–1.0	–1.0	–0.7	–0.1	0.1
Total	11,458,281	11,837,643	11,243,485	10,946,771	10,381,258	303,517	258,800	227,926	199,798	163,773					

Notes: This table reports buy-side gross notional positions and net notional positions across all reference entities as a percentage of total gross positions as of 6 January, 30 March, 29 June, 28 September, and 28 December 2012. Each row shows different counterparties: top 10 dealers, other dealers, nondealers, and centrally cleared contracts (ICE).

a few highly connected dealers should fail. We note that the transition to central clearing will be gradual owing to the large number of open bilateral positions currently held by dealers, which will probably take years to be unwound. In the meantime, we believe that tracking gross and net notional exposures is an important barometer of the safety and soundness of large security-based swap dealers.

In addition to analyzing transaction data, we conducted an analysis using quarterly positions data for 2012. We found that, on average, both dealers and nondealers tend to have a small net risk exposure to CDS contracts relative to their gross exposures. This distinction is important because even though firms may have small economic exposures (net positions), counterparty risk is determined by gross exposures. Regarding gross outstanding positions, top 10 dealers clearly accumulate and hold the largest number of gross (both buy and sell) outstanding positions. Interestingly, the picture for net positions is very different. Although most dealers have a very small net exposure to CDS contracts, several nondealers have emerged that are major net sellers of CDSs. On average, dealers are net sellers; however, by the end of our sample period, a number of significant nondealers were selling CDS protection, indicating a potential change of roles in the industry and in the CDS market. This finding suggests that dealers at large bank holding companies reduced their exposure in 2012, possibly to comply with the Volcker rule, which prohibits proprietary trading; other counterparties, such as hedge funds, have filled this gap.

With our data, we were also able to capture the beginning of contract clearing through ICE. We found that contracts tended to be cleared at an increasing rate over the sample period. As more and more contracts are cleared, it becomes increasingly important to study the network relationships of clearable and cleared contracts to see whether risk is being concentrated in certain entities. Understanding the dynamics of network topology and the effect on dealer connections of an eventual migration to central clearing will lead to a better understanding of the fragility and potential contagion of the CDS network. This knowledge can help academics and regulators identify factors necessary to prevent network fragility, and it can help practitioners learn how to incorporate the effect of dealer connections into their decision making.

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CE Qualified Activity CFA Institute 1 CE credit, inclusive of 1 SER credit

Notes

1. Dodd–Frank was enacted "to promote the financial stability of the United States by improving accountability and transparency in the financial system, to end 'too big to fail,' to protect the American taxpayer by ending bailouts, to protect consumers from abusive financial services practices, and for other purposes" (Pub. L. No. 111-203, preamble).
2. *Over the Counter Derivatives Reform and Addressing Systemic Risk: Hearings before the Senate Committee on Agriculture, Nutrition, and Forestry*, 111th Cong., S. Hrg. 111-803 (2 December 2009).
3. For purposes of this article, "swap" refers to (1) swaps regulated by the Commodity Futures Trading Commission (CFTC) and (2) security-based swaps regulated by the US SEC. The statutory requirements imposed on both markets by Title VII of the Dodd–Frank Act are similar, and in many cases, the rule-making efforts of both agencies have evolved in parallel.
4. According to Pirrong (2011, p. 6), "Widespread defaults on derivatives contracts may harm more than the counterparties on the defaulted contracts. The losses suffered by the victims of the original defaults may be so severe as to force those victims into financial distress, which harms those who have entered into financial contracts with them—including their creditors, and the counterparties to derivatives on which they owe money. Such a cascade of defaults can result in a systemic financial crisis."
5. See, for example, Gregory (2010); Duffie and Zhu (2011); Arora, Gandhi, and Longstaff (2012). Siriwardane (2015) demonstrated that the concentration of CDS protection sellers leads to higher volatility risk premiums; he also showed that capital fluctuations of the largest sellers are an important determinant in CDS spread movements.
6. Examining the 250 largest North American single-name contracts, Porter (2015) found that characteristics of many CDS reference entities that were ineligible for clearing were similar to those of other reference entities that had been approved for clearing.
7. Using a sample of 35 financial reference entities during the financial crisis (2007–2009), Shachar (2012) studied the role of dealers in providing liquidity. Using a snapshot of data for CDS positions on 30 December 2011, Peltonen, Scheicher, and Vuillemey (2013) examined the determinants of the network structure of CDS markets. Looking at all global CDS transactions between 1 May and 31 July 2010 in which at least one G14 dealer was a counterparty to the trade, Chen, Fleming, Jackson, Li, and Sarkar (2011) analyzed aggregate market liquidity and trading activity in the CDS market. Examining Federal Deposit Insurance Corporation (FDIC) call reports with off-balance-sheet bank data for the fourth quarter of 2007 and 2008, Markose, Giansante, and Shaghaghi (2012) reconstructed the network exposures of large bank holding companies.
8. The database provided by the DTCC included all transactions with at least one of the following: (1) a US reference entity, (2) a US counterparty, (3) a foreign branch of a US counterparty, or (4) a foreign affiliate of a US counterparty—all of which implies that neither foreign branches of US counterparties nor their foreign affiliates were excluded.
9. See Battiston, Delli Gatti, Gallegati, Greenwald, and Stiglitz (2009); Billio, Getmansky, Lo, and Pelizzon (2012); Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012); Acemoglu, Ozdaglar, and Tahbaz-Salehi (2013); Diebold and Yilmaz (2014). Network approaches have also been used successfully in nonfinancial markets. Csermely, London, Wu, and Uzzi

(2013) conducted a comprehensive analysis of the structure and dynamics of core/periphery networks, showing that such networks are found in cellular functions, species adaptation, and social and market changes.

10. Networks can be constructed by using such direct connections as repayment of interbank loans (Acemoglu et al. 2013); interbank payment flows (Soramäki, Bech, Arnold, Glass, and Beyeler 2007); linkage of balance sheets (Shin 2008, 2009); municipal bond transactions (Li and Schurhoff 2012); and asset commonality (Allen, Babus, and Carletti 2012)—or by using indirect connections based on principal component analysis (PCA) or causality in equity returns (Billio et al. 2012) and CDS spreads (Billio, Getmansky, Gray, Lo, Merton, and Pelizzon 2015).
11. See 79 Fed. Reg. 21; 17 C.F.R. 255 (5536–5806).
12. The main point of contention among those required to comply with the Volcker rule centered on the difficulties in differentiating between legitimate market making and proprietary trading. Because outsize net notional exposures could be viewed as speculative risk taking, dealers are expected to face regulatory pressure to maintain relatively small net notional exposures.
13. ISDA has developed a standard legal documentation format for CDS contracts that includes a list of credit event situations (ranging from bankruptcy to debt restructuring). Although contract counterparties are free to amend the ISDA definitions, the vast majority of CDS trades are covered by the standard ISDA documentation.
14. Data for the analysis included "gold record" transactions submitted to the Trade Information Warehouse. A gold record is a record whose status in the TIW is "certain," which means that the transaction has been confirmed and has satisfied certain business validation rules and other requirements of the TIW. Under TIW rules, a gold record generally represents the definitive record of the transaction and supersedes any other documentation or understanding—whether written, oral, or electronic—between the parties. See "DTCC Derivatives Repository Ltd. Operating Procedures," Appendix on TIW records, rev. 2012-1 (1 August 2012): 4–5.
15. See www.swapsinfo.org/charts/swaps/notional-outstanding?date_start=2012-01-01&date_end=2012-12-28&products=snre&suggest=&search=&type=&submit=Update+Data.
16. Because this classification is based on DTCC data, the universe of dealers may not correspond to the same set of entities that the SEC requires to register as "security-based swap dealers."
17. Using the DTCC approach for reporting CDS gross and net notional amounts, we identified market participants on the basis of counterparty family. A counterparty family typically includes all the accounts of a particular asset manager or corporate affiliate rolled up to the holding-company level. For more information, see www.dtccdata.com/products/trade-information-warehouse.
18. Transactions are cleared by ICE Clear Credit. In 2009, ICE Clear Credit became the world's first central counterparty for CDS contracts. The full list of 28 clearing members that can clear contracts through ICE Clear Credit is available at www.theice.com/clear-credit/participants.
19. The DTCC labels novated transactions as "assigned" to a different counterparty and labels cash-settled transactions as "terminated."
20. We also excluded multi-name nonindex CDS trades from our analysis. The single-name corporate and sovereign CDS contracts in our analysis represent 74.15% of all CDS transactions in 2012.
21. There are a number of different concentration measures. All are similar in that they capture the dispersion of trades across different counterparties. Bikker and Haaf (2002) surveyed various concentration measures used in the banking industry—specifically, the *k* bank concentration ratio, the Herfindahl–Hirschman Index (Herfindahl 1950; Hirschman 1964), the Hall–Tideman Index (Hall and Tideman 1967), the Rosenbluth Index (Rosenbluth 1955), the Comprehensive Industrial Concentration Index (Horvath 1970), the Hannah and Kay Index (Hannah and Kay 1977), the U Index (Davies 1979), the multiplicative Hause Index and the additive Hause Index (Hause 1977), and the Entropy Concentration Index (Jacquemin 1975). Concentration measures can be classified according to their weighting scheme and structure (discrete versus cumulative). Marfels (1971) and Dickson (1981) discussed the weighting schemes of a number of concentration ratios.
22. To mask the identities of dealers and nondealers, N represents 12 different groupings: the top 10 dealers, the set of all other dealers, and the set of all nondealers. The concentration index thus ranges from 1/11 to 1.
23. Similarly, for each dealer and nondealer i, we constructed a sell-side concentration index using the fraction of CDS contract sales to other dealers and nondealers j. Note that the concentration index is directional (i.e., buy-side concentration need not be equal to sell-side concentration). Because in our analysis the buy side and the sell side share similar results, we do not report the sell-side results for the sake of conciseness.
24. Some contracts that originated as bilateral transactions were placed in central clearing at a later date. For purposes of the results in Tables 1–3, we treated these transactions as bilateral trades. For Tables 4–11, we treated these trades as if they were centrally cleared on the transaction date.
25. For the 2012 calendar year, we identified 271 distinct trading dates owing to some trading activity on weekends and holidays.
26. We grouped top counterparties into size tiers to preserve counterparty anonymity. We sorted the tier compositions on each characteristic (buy-side/sell-side number of contracts and gross notional traded). Thus, the identities of counterparties in each tier may change for each characteristic.
27. The numbers are not exactly the same because some of the trades that were cleared in Europe (involving foreign entities on foreign reference entities) were not part of our sample. A bilateral transaction with both a US and a foreign counterparty on a foreign reference entity would normally have been included in our data; however, transactions that were centrally cleared reported the counterparties only as the initiating US counterparty and the clearinghouse. To the extent that a foreign counterparty on a foreign reference entity cleared the trade in a foreign clearinghouse, it was excluded from the data and thus the aggregate buy and sell amounts are different.
28. As shown in Tables 4–6, the top 10 counterparties for buys and sells (based on the number of contracts and the gross notional amount) were all dealers.
29. We randomized the order of dealers to mask dealer identities. Note that the labeling for the top 10 dealers is consistent in Tables 7–11.
30. The positive values along the diagonal for some of the categories (nondealers and other dealers) are an artifact of the level at which we aggregated the counterparties. For example, if two wholly owned subsidiaries transacted with one another, it would appear as if the owning entity were buying protection from itself.
31. By construction, each row sums to 100%. Columns need not sum to 100%.
32. These results are available from the authors upon request.
33. This interpretation should be viewed with a certain amount of caution. That is, although the accumulation of positions shown in Table 8 provides us with a measure of historical activity, the net notional amounts reported in Table 9 provide a sense of the economic exposure that counterparties have with respect to one another—with one caveat: The ability to interpret the net positions as true economic exposure is confounded by aggregating across reference entities. Hence, even if, on average, all counterparties have a much smaller net exposure compared with the gross notional amounts, it would not necessarily follow that their true economic exposure is correspondingly flat.
34. This result is consistent with Siriwardane (2015).

35. A more careful inspection of Table 11 shows that the flattening of the books of the top 10 dealers took place more on the buy side than on the sell side of their portfolio (meaning that the top 10 dealers decreased their net long positions more than they decreased their net short positions). As a result, the top 10 dealers went from being flat (in aggregate) to becoming net sellers, whereas other dealers went from being large net sellers to net buyers. The combined net positions of the top 10 dealers went from $438 million on 6 January to –$27.269 billion on 28 December, whereas the combined net positions of other dealers went from –$126.498 billion to $44.152 billion.

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Portfolio Similarity and Asset Liquidation in the Insurance Industry*

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

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Abstract

Certain large insurers have been designated as Systemically Important Financial Institutions (SIFI) under the assumption that the forced liquidation of their common holdings could lead to systemic risk. We construct a measure of commonality in portfolio holdings using cosine similarity, and confirm that insurers with more similar portfolios have larger common sales regardless of their size. We also document that during the financial crisis, potential SIFIs with greater portfolio similarity of illiquid and downgraded securities have greater sales commonality. Our measure is easily implementable and can be used by regulators to identify insurers who may contribute to asset liquidation channel vulnerabilities.

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

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

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

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

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

‖Goethe University Frankfurt - Center of Excellence SAFE and Ca' Foscari University of Venice, Department of Economics, 30100 Venice, Italy. Email: pelizzon@unive.it.

> "The severity of the disruption caused by a forced liquidation of Prudential's assets could be amplified by the fact that *the investment portfolios of many large insurance companies are composed of similar assets*, which could cause significant reductions in asset valuations and losses for those firms. The erosion of capital and potential de-leveraging could result in asset fire sales that cause significant damage to the broader economy." (emphasis added)
>
> Basis for the Financial Stability Oversight Council's Final Determination Regarding Prudential Financial, Inc.

1 Introduction

The global financial crisis of 2007-2009 exposed many vulnerabilities in the financial system. It highlighted the interconnectedness among financial institutions and how this interconnectedness contributed to the collapse of several prominent institutions (e.g. Lehman Brothers, Bear Stearns, Washington Mutual, Wachovia, and AIG) and to disruptions in several financial markets (e.g. stock, credit default swap, sub-prime mortgage, and money markets).

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

Although it is relatively straight-forward to measure the size of a financial institution (global assets, or for a foreign institution, U.S. total consolidated assets), there is no consensus on how to measure interconnectedness. In its designation of insurers as systemically important, the FSOC emphasizes that one component of interconnectedness arises from common asset holdings.[2] An

[1] As noted in the final rule on the *Authority to Require Supervision and Regulation of Certain Nonbank Financial Companies*, "Section 113 of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Pub. L. 111203, 124 Stat. 1376 (2010).) authorizes the Financial Stability Oversight Council to determine that a nonbank financial company shall be supervised by the Board of Governors of the Federal Reserve System and shall be subject to prudential standards... if the Council determines that material financial distress of the nonbank financial company, or the nature, scope, size, scale, concentration, interconnectedness, or mix of the activities of the nonbank financial company, could pose a threat to the financial stability of the United States." Similar criteria are used internationally by the Financial Stability Board to designate globally systemically important financial institutions (G-SIFIs) (see BIS (2014)).

[2] Regulators also consider whether insurers operational risks, reinsurance, non-traditional investments, and financing contribute to systemic risk. Harrington (2009) and Cummins and Weiss (2014) suggests that the systemic risk of property and casualty (P&C) insurers is low, while that of life insurers could be high because of higher leverage and potential policyholder withdrawals during a financial crisis. Koijen and Yogo (2016) show that life insurers use shadow reinsurance to move their liabilities from operating companies to less regulated and unrated off-balance-sheet

insurer is systemically important if it "holds assets that, if liquidated quickly, would cause a fall in asset prices and thereby significantly disrupt trading or funding in key markets or cause significant losses or funding problems for other firms with similar holdings."[3] When faced with a financial shock to either assets or liabilities, the FSOC assumes that insurers with similar holdings will rebalance their portfolios in the same fashion thereby causing asset revaluations that could transmit systemic risk throughout the economy. Consistent with this rationale, Kartasheva (2014) argues that insurers do not need to fail to propagate systemic risk; it may be sufficient for them to "fire sell" assets to produce a significant systemic impact.

This rationale is supported by a number of studies, which document that sales by insurers exert downward pressure on prices. Ellul, Jotikasthira, and Lundblad (2011), Ambrose, Cai, and Helwege (2008) and Manconi, Massa, and Yasuda (2012) show that regulatory capital constraints induce a collective need for insurers who hold downgraded securities to sell them, and these actions can lead to fire sale prices. Nanda, Wu, and Zhou (2017) find that when a bond is held by more regulatory-constrained insurance companies, the effect of a fire sale on bond yields is more pronounced. Chiang and Niehaus (2016) document that life insurers tend to herd in the buying and selling of corporate bonds and show that bond returns are abnormally low during the quarter when insurers exhibit high sell-side herding. Cai, Han, Li, and Li (2016) conclude that "insurance companies, the largest investor group of corporate bonds, have a greater tendency, in general, to trade in sync than mutual funds and pension funds."

In this paper, we propose a measure of interconnectedness among insurers based on the cosine similarity of their portfolio holdings across all asset classes and security issuers. To construct our measure, we use data from 2002 to 2014 from the National Association of Insurance Commissioners (NAIC), which requires insurers disclose their portfolio holdings and trades at the individual security level. Our measure of portfolio similarity is more comprehensive than prior studies since it reflects insurers' interconnectedness across their entire portfolio, not just across their publicly

entities within the same insurance group. These "shadow reinsurer" transactions do not decrease life insurers' risk as liabilities stay within the same insurance group. Reinsurance can also be a source of interconnectedness (Cummins and Weiss (2014) and Park and Xie (2014)), as can be insurers' increased exposure to derivatives (Geneva Association (2010) and Grace (2010)) and increased reliance on short-term funding (Geneva Association (2010)).

[3] See *Basis for the Financial Stability Oversight Council's Final Determination Regarding Prudential Financial, Inc.* available on the FSOC website (FSOC (2013)). As of the writing of this paper, the FSOC has designated four nonbank financial institutions (three of them are insurance companies) as SIFIs: MetLife, Inc., American International Group, Inc. (AIG), General Electric Capital Corporation, Inc. and Prudential Financial, Inc.

traded corporate bond holdings.[4] Our method, therefore, can measure the similarity in re-balancing across all asset classes and security issuers. For example, it is well-known that during the global financial crisis investors sold troubled assets and moved into safe assets such as Treasury securities.

We use cluster analysis at the primary asset class level and show that insurers' asset allocation decisions can be characterized by only three distinct strategies based on the dominant primary asset class held: 1) corporate bonds, municipal bonds, and Government Sponsored Entity (GSE) securities, 2) corporate bonds, and 3) equity. We find that these strategies tend to be long-term in nature and do not vary much over the business cycle.

Next, we examine the determinants of pairwise portfolio similarity using a multivariate approach that controls for insurer pair characteristics. We show that both asset class and issuer portfolio similarity is higher when both insurers in a pair are in the same line of business (life or P&C). This finding is consistent with the notion that similarity on the liability side of the balance sheet is associated with similarity on the asset side as well.

In line with regulatory guidelines, we find that size is an important determinant interconnectedness at both the asset class and issuer level, irrespective of whether an insurer pair meets the SIFI designation size threshold.[5] Pairs of insurers that are both SIFI (PSIFI) or both non-PSIFI have greater portfolio similarity.

Concentration has also been proposed as a useful metric to identify systemically important financial institutions (Haldane and May (2011) Gai, Haldane, and Kapadia (2011) and Allen, Babus, and Carletti (2012)). In terms of portfolio concentration, we find conflicting results on the importance of concentration in predicting portfolio similarity. However, for PSIFI insurer pairs, we find a negative association between portfolio similarity and concentration at both the asset class and issuer level. This finding implies that for the largest insurers in our sample diversification increases portfolio similarity. This is consistent with a growing literature (Castiglionesi and Navarro (2008), Wagner (2010), Ibragimov, Jaffee, and Walden (2011), Wagner (2010) and Cont and Wagalath (2016)) that argues that although diversification of assets reduces each institution's individual

[4]We estimate that publicly traded corporate bonds comprise only a fifth of the assets in the insurance industry. Based upon data from Schedule D and TRACE for 2014, we estimate that life and P&C insurers hold \$1.36 trillion of publicly traded corporate bonds (corporate bonds that traded at any time during that year). The Federal Reserve's Flow of Funds tables in 2014 indicate that these insurers held \$6.3 trillion of debt and equity securities.

[5]We define a PSIFI as having \$50 billion or more in consolidated assets in at least one year of our sample period. This definition is similar to that used by the FSOC as a size threshold for nonbank SIFIs and for determining global systemically important insurers (IAIS (2013) and IAIS (2015)).

probability of failure, it can make the potential for correlated selling higher.

Our main analysis examines whether our measure of interconnectedness can predict asset liquidation among insurers. We use quarterly buy and sell transactions at both the asset class and issuer levels to construct a measure of common sales as the dot product of the dollar amount of net sales (sales minus purchases) for each pair of insurers. After controlling for insurer pair characteristics, we find that the portfolio similarity of an insurer pair significantly predicts the magnitude of common future sales, regardless of SIFI status.

We also document that larger insurers have larger common sales, which suggests that an underlying characteristic related to size, such as the complexity of product lines and the propensity to engage in non-core insurance activities (e.g. securities lending, derivatives, reliance on reinsurance business etc.), may make larger insurers more susceptible to common shocks and hence, more prone to similar re-balancing decisions.

We test whether regulatory capital-constrained insurers attempt to improve their capital position by re-balancing their investment portfolios. We interact the measure of portfolio similarity with an indicator variable equal to 1 if both insurers in a pair have low risk-based capital (RBC) ratios, and zero otherwise. We find that insurers pairs, particularly non-PSIFI pairs, that have high portfolio similarity and low RBC are more likely to sell the same types of assets. We do not find that RBC affects the selling behavior of PSIFIs mainly because these insurers tend to be well capitalized.

The liquidity and/or credit quality of an insurer's holdings may also influence its selling behavior particularly in times of market stress, and we capture their effects by decomposing an insurer's portfolio into the cosine similarity of 1) liquid and illiquid asset classes and 2) downgraded and non-downgrade issuers.[6] In all specifications, the coefficients on each of the decomposed portfolio similarities – liquid, illiquid, downgraded, and not downgraded – are positive and highly significant. This implies that the amount of correlated selling is affected by the portfolio similarity of all types of securities in the pair's portfolios and not just those securities that have lower liquidity or whose issuers were subsequently downgraded.

[6] We consider liquid securities to be those that fall within the following primary asset classes: equity, mutual fund shares, US government securities, GSE securities, and sovereign bonds. Illiquid securities are those that fall within the following primary asset classes: corporate bonds, municipal bonds, Residential Mortgage-Backed Securities (RMBS), Commercial Mortgage-Backed Securities (CMBS) and all other non-mortgage asset-backed securities (ABS). Downgraded (not downgraded) issuers are security issuers that are (are not) downgraded in the following year.

We further test whether portfolio similarity increases the amount of common sales during the financial crisis and find some evidence of greater sales similarity during the crisis for insurers, other than PSIFI pairs, who hold more similar portfolios of liquid assets and who both have low RBC.[7] More importantly, we show that PSIFI pairs, who have greater portfolio similarity of illiquid assets or downgraded issuers, have greater selling similarity during the financial crisis. This finding provides support for the combined use of size and interconnectedness by regulators in predicting the potential for correlated selling in these types of assets during market stress.

Next, we examine whether public market information such as return covariance is related to common sales and can be used as a substitute for portfolio similarity. A number of papers have proposed covariance as a measure of interconnectedness (Billio, Getmansky, Lo, and Pelizzon (2012), Neale, Drake, Schorno, and Semann (2012), and Brunetti, Harris, Mankad, and Michailidis (2015)).[8] We show that return covariance for pairs of publicly traded insurer holding companies has no relationship to net sales similarity at the asset class level but can predict the magnitude of similar selling at the issuer level. Our measure of portfolio similarity remains statistically significant even when return covariance is included in the specification. This finding suggests that covariance may not fully capture the effect of interconnectedness on the transmission of systemic risk through the asset liquidation channel. These results highlight an additional benefit of our measure: it does not rely on an insurer having publicly traded equity and thus, can be used to understand the interconnectedness of private insurers when market-based measures of systemic risk are unavailable.

Finally, we propose an insurer-level portfolio similarity measure, computed as the average portfolio similarity of an insurer with all other insurers in our sample, to identify specific insurers that might contribute to the asset liquidation channel of systematic risk transmission. We show that this measure can be used to predict the extent to which an individual insurer will sell more in common with other insurers even after controlling for the insurer's size and dollar value sold. Thus, we suggest that this measure can be used in tandem with other measures of potential systemic risk to identify candidates for SIFI designation.

Overall, our results indicate that the interconnectedness of insurers' portfolios, as measured by

[7]Greater selling of liquid but not illiquid assets is consistent with the findings of Ellul, Jotikasthira, Lundblad, and Wang (2015).

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

the cosine similarity of holdings, captures attributes an aspect of interconnectedness that other simple measures such as portfolio concentration, return covariance, and size do not. More importantly, our measure predicts commonality in asset liquidation across insurers making it relevant to regulators who are tasked with monitoring systemic risk in the economy.

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

2 Data

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

Portfolio holdings and both sales and purchases are reported at the individual security (9-digit CUSIP) level. For each insurer, we aggregate this information to the security issuer and to the asset class level.[9] We use the first 6 digits of each CUSIP as the issuer identifier and aggregate the holdings, sales and purchases of securities with the same 6 digit CUSIP.[10] We construct quarterly net sales at the issuer level as sales minus purchases, excluding negative values.

Before aggregating holdings, sales and purchases to the asset class level, we first categorize each security into one of ten primary asset classes: (1) U.S. government debt, (2) GSE debt (including

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

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

mortgage-backed securities), (3) municipal debt, (4) sovereign debt, (5) corporate debt, (6) private-label RMBS, (7) private-label CMBS, (8) private-label ABS, (9) equity (common and preferred stock), and (10) mutual fund shares. We identify RMBS and CMBS using the NAIC-provided list of PIMCO- and BlackRock-modeled securities.[11] We classify all 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 debt, municipal debt and equity using the issuer's industry or sector information reported in Schedule D. This process yields 34 unique asset classes.[12] (See Appendix A for a list of these asset classes.) We then aggregate holdings, sales and purchases by each asset class. We compute quarterly net sales for each asset class as the difference between sales and purchases excluding negative values.

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, thus creating strong connections among the members of a group. We, therefore, conduct the majority of 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.

For some of our analysis, we require stock return data, which is only available at the holding company level. Typically, a holding company owns several insurer groups. To aggregate Schedule D and balance sheet data to the holding company level, we match insurer groups to company names in CRSP/Compustat Merged and are able to find matches for between 73 and 99 holding companies (depending on the calendar year). For each holding company, we collect daily holding period returns from CRSP.

We also categorize insurers as P&C, life, or other (e.g. health, fraternal, and title) if at least half

[11]The NAIC changed its capital assessment methodology for certain asset classes by replacing credit ratings as the measure of expected loss with valuation-based loss estimates from PIMCO for RMBS and BlackRock for CMBS. The NAIC publishes the list of PIMCO- and BlackRock-modeled securities annually. For more information on this regulatory change, see Hanley and Nikolova (2015).

[12]We categorize corporate bonds and equity as undefined if issuer industry or sector is missing or conflicting.

of the insurers' portfolio assets are held in a given year by companies in the group that are in that line of business.[13] The majority of insurers in our sample are P&C companies (1,746) as compared to life (635). In order to examine whether systemically important insurers are more likely to have similar portfolios and sell similar assets, we also classify insurers as Potentially Systemically Important Financial Institutions (or PSIFIs) if they have more than $50 billion in total assets excluding assets held in separate account in at least one year of the sample. Based on this size threshold, we identify 38 insurers in our sample as potential candidates for SIFI designation by the FSOC.[14]

2.1 Sample Characteristics

Table 1 presents descriptive statistics for our sample of insurers. (Appendix B provides detailed definitions of the variables used in our analysis.) For each insurer, we compute the time-series average of each variable across the sample period and report the cross-sectional mean, median, and standard deviation. The average total assets of all 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, PSIFIs have significantly more assets ($99.8 billion) compared to non-PSIFIs ($0.87 billion). The average insurer's investment portfolio is $1.65 billion. As with total assets, life insurers have larger portfolios than P&C insurers, and PSIFIs have larger portfolios than non-PSIFIs.

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

[13]The number of insurers in the "other" category is small and we do not report summary statistics separately for this type.

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

as indicated by the standard deviation of corporate bonds, GSE securities and equity, in particular.

Figure 1 summarizes the time-series variation of the insurance industry's aggregate holdings and indicates that shifts in and out of asset classes occur through time. Over our sample period, the proportion of the aggregate insurance portfolio allocated to U.S. government and ABS securities increases slightly. The figure also shows that insurers' holdings of RMBS and CMBS increase in the period leading up to the financial crisis and then gradually decrease consistent with the evidence presented in Hanley and Nikolova (2015).

The average insurer in our sample holds 380 different securities issued by 250 separate issuers. The median number of securities issuers held is less than half of the sample average, implying that some insurers invest in significantly more securities than others.

Table 1 shows that some of this variation in holdings by asset class is related to insurer type. Life insurers invest in more securities and issuers than P&C insurers, and their portfolios are more heavily weighted toward corporate bonds and asset-/mortgage-backed securities, and less toward municipal bonds and equity.

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

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

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

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

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

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

Table 1 reports the cross-sectional mean, median and standard deviation of insurers' time-series averages of the two concentration measures. The average asset class concentration in our sample is 0.31 and the average issuer concentration is 0.16. Life and P&C insurers have similar portfolio concentrations. Finally, PSIFIs' portfolios are less concentrated than those of non-PSIFIs at both the asset class and issuer level indicating that PSIFIs' portfolios are more diversified.[15]

3 Portfolio Composition Using Cluster Analysis

In this section, we examine the portfolio strategies of insurers at the asset class level using cluster analysis.[16] We are interested in whether insurers differ in their portfolio allocation strategies and whether their strategies change over time. Cluster analysis allows us to separate insurers into subgroups (clusters) that are likely to have closer connections with each other than with those outside the cluster. As shown in Appendix C, the cluster validation process produces three distinct clusters suggesting that firms in the insurance industry employ only a small number of portfolio strategies.

The average structure of the three clusters is displayed in Figure 2. Cluster 1 of the sample is diversified across the primary classification of asset classes. Cluster 2 is mainly invested in corporate bonds and GSE securities. Cluster 3 is dominated by equity. In terms of the number of insurers in each cluster, Cluster 1 and Cluster 2 are evenly split with approximately 45% of the sample of all insurers in each cluster. The remaining 10% of insurers are in Cluster 3. If we apply the cluster analysis separately in each year, the optimal number of clusters remains at three and the composition of each cluster is relatively stable.[17]

The cluster analysis of insurer portfolios suggests that insurers are very similar in their portfolio composition and therefore, potentially in their trading strategy. The low number of unique asset allocation strategies among insurers differentiates them from mutual funds that follow many different investment strategies. Figure 3 shows the distribution of PSIFIs and non-PSIFIs in each cluster.

[15] This result is not surprising given the large size of the average PSIFI's portfolio.

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

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

There is a clear distinction between the portfolio allocation strategies of PSIFIs and those of non-PSIFIs. PSIFI's portfolios mostly resemble Cluster 2, which is dominated by corporate bonds and GSE securities. Non-PSIFI's portfolios are dominated by Cluster 1 which is more diversified across different primary asset classes. These results are consistent with statistics presented in Table 1. The different portfolio strategies employed by PSIFIs and non-PSIFIs highlight the potential for important differences in rebalancing behavior during times of stress. In the next section, we discuss a methodology that captures the similarity of portfolio choices among insurers at a more granular level.

4 Portfolio Similarity

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

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

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

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

where $w_{i,t}$ is insurer i's and $w_{j,t}$ is insurer j's vector of weights at calendar t year end.

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

Figure 4 shows the time series of the average pairwise portfolio similarity at the asset class and security issuer level for the sample of all insurers and for the subsamples of PSIFI pairs or non-PSIFI pairs. We define the variable *PSIFI_Pair* equal to 1 if both insurers are classified as PSIFIs and 0 otherwise. We define *Non-PSIFI_Pair* equal to 1 if both insurers are classified as non-PSIFIs and equal to 0 otherwise. Since non-PSIFI pairs make up the majority of the insurers in our sample, their average portfolio similarity closely mimics that of all insurers at either the asset class or security issuer level. PSIFI pairs have higher asset class and security issuer similarity than non-PSIFI pairs. PSIFI pairs' asset class similarity does not fluctuate much over time, while that of non-PSIFIs decreases. At the security issuer level, non-PSIFI pairs' portfolio similarity is relatively constant, while PSIFI pairs have become more similar over time. Interestingly, the divergence in portfolio similarity between PSIFIs and non-PSIFIs increases after the financial crisis.

Table 2 provides summary statistics for portfolio similarity measures for the whole sample of insurer pairs as well as for PSIFI and non-PSIFI pairs. Similarities are calculated at the asset class and security issuer level In addition, we construct the similarity between pairs of insurers' portfolios using liquid or illiquid asset classes, and downgraded or not downgraded issuers.

We classify the holdings of insurers as being liquid if they belong to the following primary asset classes: equity, mutual fund shares, U.S. government securities, GSE securities, and sovereign bonds. We consider the following asset classes to be illiquid: corporate bonds, municipal bonds, RMBS, CMBS and ABS. We then construct the portfolio similarity between pairs of insurers using asset classes that are either categorized as liquid, *Similarity_AC_Liquid*, or illiquid, *Similarity_AC_Illiquid*.

The average asset class similarity between a pair of insurers, *Similarity_AC*, is 0.43. However, PSIFI pairs have much larger average portfolio similarity at the asset class level (0.65) than non-PSIFIs (0.44). The average similarity between a pair of insurers' at the security issuer level, *Similarity_ I*, is much lower (0.13) than *Similarity_ AC* because there are many more issuers (250) than asset classes (34). The portfolio similarity using security issuers is again higher (0.18) for PSIFI pairs than non-PSIFI pairs (0.13).

Our determination of whether or not an issuer is downgraded uses credit rating information from DataScope. We identify the year in which a security is first downgraded from investment grade (IG) to non-investment grade (NIG) by S&P, Moody's or Fitch. This information is aggregated to the security's issuer level. We define a downgraded issuer as an issuer that has at least one of its securities downgraded from IG to NIG in a given year. We then construct the portfolio similarity between pairs of insurers using only downgraded issuers, *Similarity_I_Downgraded*, or only not downgraded issuers, *Similarity_I_NotDowngraded*.

On average, we do not find large differences in the portfolio similarities of all insurers using liquid and illiquid asset classes, or downgraded and not downgraded issuers. However, PSIFI pairs tend to have greater portfolio similarity for both liquid and illiquid asset classes compared to non-PSIFI pairs. The same relationship holds true when examining the average portfolio similarity using downgraded or non-downgraded issuers. Consistent with the FSOC's concern about the potential for correlated asset liquidation of PSIFIs, the average portfolio similarity of downgraded securities is much larger (0.41) for PSIFI pairs than for non-PSIFI pairs.

To assess the extent to which insurers sell similar asset classes or security issuers, we construct a measure of dollar commonality in sales, (*$ Sales Similarity*). Specifically, for each insurer, we create a vector of quarterly net sales (sales minus purchases) of each asset class or issuer of securities. If an insurer does not sell assets in a particular asset class or does not sell securities issued by a particular issuer, the element in the vector is set to 0.[18] Our measure, therefore, can capture the similarity in the decision of insurers to both sell the same assets as well as to *not* to sell the same assets.

It is important to note that dollar net sales similarity is based on dollar net sales amounts and is not normalized by holdings or total sales. In this way, we make sure that our results are not driven by small sales (that might have larger normalized sales fractions). Thus, the dot product of net sales is intended to capture the sales intensity of a pair of insurers.[19]

Table 2 provides statistics on the average dollar net sales similarity. The average *$ Sales Similarity* at the asset class level is almost 28 and at the security issuer level it is 26. Note that the

[18] If an insurer does not sell anything at all during the quarter, we cannot compute the dot product of vectors of quarterly net sales, as all elements in vectors are set to zero. Therefore, these insurers would not be included in our tests.

[19] Our results are robust to using the cosine similarity of insurer pairs using weighted or proportional dollar value of net sales.

vector of dollar sales similarity does not have a unit of 1 and thus, the dot product of an insurer pair's net sales is not bounded between 0 and 1.

In addition, the table indicates that PSIFI pairs have, on average higher, dollar net sales similarity, both at the asset class (36.62) and security issuer (34.55) levels compared to non-PSIFI pairs (27.43, and 25.94, respectively). Since we are using dollar sales, the *$Sales Similarity* for PSIFI pairs is not surprising given their larger size.

Overall, these summary statistics show that PSIFI pairs tend to have larger portfolio holdings similarity compared to non-PSIFI pairs, especially within the illiquid and downgraded segments of their portfolios. They also tend to have larger sales similarity at both the asset class and issuer level. It is important to note that there is a high degree of variability in portfolio holdings similarity and dollar net sales similarity across issuer pairs, whether PSIFI or not.

4.1 Determinants of Portfolio Similarity

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

We estimate OLS regressions where the dependent variable is the pairwise holdings similarity measure in a given year defined at either the asset class, *Similarity_AC* in Models (1) - (3), or security issuer level, *Similarity_I* in Models (4) - (6) in Table 3. In Models (1)-(3), we find that the portfolio similarity between two insurers, at the asset class or security issuer level, is greater if they are both life insurers or both P&C insurers. This makes sense intuitively because insurers typically make asset allocation decisions with their liability risk in mind. Since insurers in the same line of business have similar liability structures, we would expect them to have more similar types of investments. Examining portfolio similarity at the security issuer level in Models (4)-(6), we find somewhat different results. For the sample of all insurers, a P&C pair has more similar portfolio holdings but a life insurer pair of insurers does not. When examining PSIFI pairs and non-PSIFI pairs separately, we show that this result is limited to non-PSIFI life pairs and reverses for PSIFI life pairs.

The portfolio holdings similarity between two insurers is greater if both insurers have the same PSIFI classification regardless of whether this is measured at the asset class or security issuer level. Moreover, as can be seen in Models (2) and (5), this relationship appears to be driven by larger insurer pairs as the coefficient of *Prod_Size* is positive for the sample of non-PSIFI pairs.[20] Thus, larger insurer pairs are more similar to each other regardless of SIFI status. The could be due to the fact that larger insurers are more likely to engage in non-core insurance activities and have more complex product lines. This, in turn, may make larger insurers more likely to be affected by similar shocks.

Generally, the less concentrated (more diversified) the portfolio, the more similar is the portfolio similarity. This is particularly true for PSIFI pairs, which always have greater portfolio similarity when their concentration is low regardless of whether it is measured at the asset class or security issuer level. Recent theoretical works have shown that full diversification may not be optimal from a systemic risk perspective because it can lead to financial contagion. For example, Allen, Babus, and Carletti (2012), Castiglionesi and Navarro (2008), Ibragimov, Jaffee, and Walden (2011), Wagner (2010)), Ibragimov, Jaffee, and Walden (2011), Wagner (2010), and Beale, Rand, Battey, Croxson, May, and Nowak (2011) show that even though diversification of assets reduces each institution's individual probability of failure, it can make systemic crises more likely. An exception to our finding of a positive relation between portfolio diversification and similarity is in Models (4) and (5) for the sample of all insurer pairs and non-PSIFI pairs when similarity is measured at the security issuer level. In this case, these insurer pairs tend to have greater portfolio similarity if they are more concentrated. This may be due to the propensity for smaller insurers to invest in only a few well-known issuers and/or to draw from the same pool of advisors who recommend the same investments.

Overall, the findings of this table point to the important role that size and business lines play in the similarity of portfolio holdings. Correlated holdings of securities may lead to correlated

[20] This finding is confirmed if we characterize pairs of insurers as both large or small based upon the median portfolio asset size using an indicator variable. For non-PSIFIs, pairs of large insurers have greater portfolio similarity while pairs of smaller insurers have lower portfolio similarity.

re-balancing in times of stress. Next, we examine whether portfolio holdings similarity can predict the common selling by insurers and could affect the asset liquidation channel of systemic risk transmission.

5 Portfolio Similarity and Asset Liquidation

We begin our analysis of similarity of net sales by examining the variation in *$ Sales Similarity* at the asset class and security issuer levels. Figure 5 presents the quarterly time-series averages of this variable for the full sample of insurer pairs as well as PSIFI and non-PSIFI pairs. At both the asset class and security issuer levels, we observe much larger dollar net sales similarity for PSIFI pairs compared to non-PSIFI pairs. It is clear from the graph that most of the selling by insurers is done in the last quarter of the year and therefore, we use quarter fixed effects in our multivariate analysis to control for this pattern. Interestingly, we do not see an increase in *$ Sales Similarity* during or around the recent financial crisis. We further explore crisis dynamics in a later sub-section below.

In Table 4, we investigate whether the portfolio similarity of a pair of insurers can predict their sales similarity. We hypothesize that insurers with more similar portfolios will sell similar assets consistent with the theoretical work of Allen, Babus, and Carletti (2012). Specifically, we estimate an OLS regression where the dependent variable is *$ Sales Similarity* and the main independent variable of interest is the prior year's portfolio holdings similarity. In addition, we control for other pair characteristics and include year-quarter fixed effects.

The findings in Table 4 are consistent with our prediction. At both the asset class and security issuer level, in Models (1) through (6), we find a significant relationship between the similarity in portfolio holdings and the similarity in dollar net sales. Pairs of insurers that have more similar portfolios are more likely to sell similar assets.

We further investigate whether larger insurer pairs have larger sales similarity by using $Prod\_Size$. We find that the joint size of an insurer pairs' holdings is a reliable predictor of the magnitude of net selling similarity. Even though it is intuitive that larger insurers should sell a greater dollar amount of similar assets, it is important to emphasize that even after controlling for $Prod\_Size$, we find a very strong relationship between the similarity in portfolio holdings and the similarity of net sales. Therefore, size is an important variable in predicting selling behavior and is consistent with the criteria that the FSOC uses to designate systemically important nonbank financial institutions. However, it is not the only variable that captures the joint selling behavior of insurers. Our results indicate that portfolio holdings similarity is also important when monitoring the asset liquidation channel and the potential systemic impact of fire sales.

In addition to portfolio similarity and size, other insurer characteristics are also useful in predicting sales similarity. In Table 4, the combined business line of insurers depends on whether the selling similarity is measured at the asset class or insurer level. At the asset class level, P&C (life) insurer pairs have greater (lower) sales similarity. At the security issuer level, life (P&C) insurer pairs have greater (lower) sales similarity.

We further investigate whether the joint concentration of the insurer pair's portfolio, either at asset or security issuer level, leads to more similar selling. We find a strong relationship between the combined concentrations of the insurer pair's portfolio and the magnitude of common net sales. However, this relationship is not present in the PSIFI pairs regressions. Although concentration has been proposed as a potential metric to identify systemically important financial institutions (Haldane and May (2011) Gai, Haldane, and Kapadia (2011) and Allen, Babus, and Carletti (2012)), our results suggest that it is not a significant determinant of joint PSIFI selling behavior once portfolio similarity is taken into consideration. Because our measure of portfolio similarity remains significant even after the concentration of the assets is included in the specification, this means that concentration measures alone may not fully capture the effect of portfolio similarity on net sales, particularly for non-PSIFI insurers.

Finally, we examine the effect of PSIFI status on the selling behavior of insurers in Models (1) and (4). We find that when two insurers are both PSIFIs, they have significantly greater dollar net sales similarity. For non-PSIFI pairs, the relationship is negative at the asset class level and positive at the security issuer level. Overall, our findings confirm that portfolio similarity is an important determinant of sales similarity and this relationship is stronger when both insurers are large and PSIFIs. Thus, our measure of portfolio interconnectedness appears to capture information about future sales that could be used to monitor insurers and identify those that contribute more to the transmission of systemic risk through the asset liquidation channel. Next, we examine whether these relationships may be driven by insurers with low regulatory capital.

5.1 Risk-Based Capital Ratios

The literature has documented that entities subject to capital regulation have an incentive to engage in asset sales when capital is depleted. In particular, insurers replenish capital by selling downgraded assets (Ellul, Jotikasthira, and Lundblad (2011)) and/or by selling liquid assets (Ellul, Jotikasthira, Lundblad, and Wang (2015)). In this section, we examine whether our findings on the relationship between portfolio similarity and sales similarity are due to capital constrained insurers.

We assess the extent to which an insurer is regulatory-capital constrained through its ratio of statutory to risk-based capital (RBC ratio). A larger RBC ratio can potentially reduce the need for asset sales and provide a buffer against an asset or liquidity shock. To allow for non-linearity in the relationship between RBC and sales similarity, we consider both the level of RBC and whether RBC is extremely low. We include the natural logarithm of the product of RBC for the insurer pair (*Prod_RBC*) and construct a pairwise indicator variable, (*RBC_Low_Pair*), equal to one if both insurers' RBC ratios are at or below the bottom quartile of RBC in the sample.[21]

We hypothesize that the selling behavior of pairs of insurers will be affected if both are capital constrained and have similar portfolios. Therefore, we would expect that an interaction term between portfolio similarity and low RBC, *Similarity*RBC_Low_Pair*, will be positive and significant.

The results in Table 5 present evidence on the effect of regulatory capital constraints on *$ Sales Similarity*. The coefficient of *Prod_RBC* is significantly negative, and the coefficient of *RBC_Low_Pair* is significantly positive, for the sample as a whole and for non-PSIFI pairs in Models (1), (2), (4), and (5). This significance indicates that when the combined RBC ratio of the insurer pair is lower or when both insurers are capital constrained, they tend to sell more of the same asset classes or security issuers. When RBC is interacted with portfolio similarity, we find that greater portfolio similarity for capital constrained insurers leads to greater sales similarity in the sample of all insurers and non-PSIFI pairs but only at the asset class level. This means that insurers, other than PSIFIs, who have similar regulatory capital and high portfolio similarity are likely to sell a greater amount of securities in the same asset class but not necessarily the same security issuers. Risk-based capital is not a significant factor for predicting sales similarity in the PSIFI pairs regressions (Models (3) and (6)). This result is not surprising because large insurers

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

tend to be very-well capitalized and thus, their selling behavior is unlikely to be affected by RBC. Indeed, only 36 PSIFI pairs (out of 26,432) both have low RBC.

We document that there is a stronger relationship between asset class portfolio similarity and sales similarity when both pairs of insurers have inadequate capital. Capital adequacy affects the selling behavior of insurers who have similar asset class portfolios. Our results suggest that non-PSIFIs may be liquidating the same asset classes when they need to replenish capital. Next we examine whether our findings are driven by either the liquidity or credit quality of the assets.

5.2 Liquidity and Downgrades

In this section, we test whether the similarity in portfolio holdings of illiquid or downgraded assets has the potential to be disruptive to markets, particularly for regulated entities, if they need to replenish capital. If insurers who hold similar illiquid assets also need to sell more of these assets, it is probable that such sales will have a large price impact and increase the probability of a downward spiral in valuations (Brunnermeier and Pedersen (2009), and Cont and Wagalath (2015)).

A similar logic applies to the expected effect of the portfolio similarity of downgraded assets on selling behavior. A number of studies document that the asset sales of distressed securities of capital constrained insurers tend to depress prices (Ellul, Jotikasthira, and Lundblad (2011) and Merrill, Nadauld, Stulz, and Sherlund (2013)). The findings of these papers may explain why some insurers have been designated as systemically important. We analyze whether the relationship we document between portfolio similarity and sales similarity may be due only to the interconnectedness of insurer pairs' portfolio holdings of downgraded assets.

Figure 6 shows the proportion of the portfolio holdings and sales that are comprised of illiquid asset classes and downgraded issuers. In Panel (a), approximately 70% of insurers holdings are classified as illiquid, and this proportion is relatively constant over the sample period. Panel (b) shows a significant time trend in the percentage of insurers' holdings that are classified as downgraded. Not surprisingly, the proportion of downgraded issuers increases is highest during the financial crisis and reaches approximately 15% of holdings. The time-series changes in the credit quality of insurers' portfolio points to the possibility that the magnitude of sales similarity may be affected by only a portion of an insurer's portfolio.

Table 6 presents the analysis of the relationship between dollar net sales similarity and the decomposed portfolio similarity based on liquidity or credit quality. As can be seen from the table, differences in liquidity or credit quality are not driving our results. In all specifications, the coefficients on each of the decomposed portfolio similarities: liquid, illiquid, downgraded, and not downgraded, are highly significant and positive. We interpret these relationships as evidence that the amount of correlated selling is affected by the portfolio similarity of all types of asset classes in an insurer pair's portfolio and not just those asset classes that have lower liquidity or those issuers that have been downgraded.

It is possible, however, that insurer pairs with similar portfolios of illiquid or downgraded securities are more likely to sell the same asset class or security issuer when both insurers need to rebuild capital. To test this theory, we interact our decomposed portfolio similarity measures with *RBC_Low_Pair*. If regulatory capital depletion is the reason for selling downgraded or illiquid securities, we expect to find that the coefficient on the interaction term between illiquid and downgraded portfolio similarity and low RBC will be positive and significant. Only in Model (2), do we find evidence that capital constraints matter for the magnitude of common sales of illiquid asset classes. Non-PSIFI insurer pairs with similar portfolios of illiquid securities and who both have low capital have higher dollar net sales similarity. Consistent with Ellul, Jotikasthira, Lundblad, and Wang (2015), dollar net sales similarity is greater when either all insurer pairs or non-PSIFI insurer pairs have more similar portfolios of liquid assets and low RBC. Thus, pairs of insurers who are capital constrained, other than PSIFI pairs, sell both liquid and illiquid similar assets.

For downgraded securities in Models (4) and (5), we find that when both insurers in a pair have low RBC and similar portfolios of either downgraded or not downgraded issuers, the magnitude of selling of similar assets decreases, not increases. Overall, the results of this section suggest that neither similarity of liquidity nor credit quality of the insurer pair's portfolio is driving our results. We next explore whether the portfolio similarity and sales similarity relationship we document changes during the financial crisis.

5.3 The Financial Crisis

Given the concern about the fire sales by regulated entities during the financial crisis, it is natural to examine whether our findings are due only to this time period. We create indicator variables equal to 1 for the following time periods: (1) *Pre-Crisis* from 2002-2006, (2) *Crisis* from 2007 to 2009, and (3) *Post-Crisis* from 2010 to 2014. The variable is equal to 0 otherwise.

In Table 7, we interact our measure of portfolio similarity with both *Crisis* and *Post-Crisis* and examine whether the magnitude of selling similarity is greater during three periods. We find little effect that the selling of similar assets increased during the crisis. The coefficient of *Crisis* is generally insignificant and is even negative in Model (6). In other words, PSIFI insurer pairs have lower correlated selling during the financial crisis. We find weak evidence that greater asset class similarity during the crisis, is associated with larger dollar net sales similarity in Model (1) but find no statistical significance once the sample is split between non-PSIFI and PSIFI pairs.

We document two interesting effects in the post-crisis period. First, at the asset class level, PSIFI pairs with greater portfolio similarity sell more of the same asset class. Second, this is partially offset by the fact that the relationship between security issuer portfolio similarity and sales similarity is weaker after the financial crisis. This may mean that insurers are actively attempting to mitigate the effect of correlated holdings on asset sales during this time period.

Next, we use portfolio similarity decomposed by credit quality and liquidity to determine whether selling behavior is affected more by certain aspects of insurers' portfolios during and after the crisis. The results are presented in Table 8.

During the crisis, pairs of insurers that have high portfolio similarity of liquid, but not illiquid asset classes, have greater sales similarity. This indicates that any price pressure that could occur as a result of correlated selling by insurers will occur in liquid, not illiquid assets. Khandani and Lo (2007) show that many quantitative long/short equity funds with relatively liquid strategies lost money due to having correlated portfolios during the financial crisis. After the crisis, insurers holding liquid assets tend to sell more similarly compared to insurers holding illiquid assets. Interestingly, the results for PSIFIs are opposite, and both during the crisis and post-crisis, PSIFIs holding more similar illiquid assets tend to sell more similarly. This finding may be of particular interest to regulators who are concerned about asset liquidation, especially during a crisis and when illiquid assets may have to be sold. The fact that we find a significant relation between larger common sales by PSIFI pairs and their holdings of illiquid assets both during and after the financial crisis is very important as it provides the channel through which fire sales can occur in times of market stress.

During the crisis, we do not find a stronger relationship between the portfolio similarity of downgraded issuers and sales similarity.[22] However, for PSIFIs we find that the relationship between downgraded issuer holdings and sales is stronger during the crisis. Post-crisis we find that the relationship between similar holdings of both downgraded and not downgraded issuers and dollar net sales similarity decreases.

In conclusion, concerns about correlated selling of illiquid and downgraded securities for PSIFIs appear to be validated in our results. During the financial crisis, PSIFIs with greater portfolio similarity of illiquid and downgraded securities have higher sales similarity, and the relationship for illiquid assets remains strong even after the crisis ends. Hence, for PSIFIs, the relationship between holding similarity and sales similarity would have been driven by the downgraded portion of their portfolios. Note the post-crisis relationship between holding similarities of downgraded issuers for PSIFIs and sales is no longer significant as PSIFIs disposed of most downgraded issuers during the crisis. This result is consistent with Figure 6.

5.4 Return Covariance and Net Sales Similarity

In this section, we examine whether portfolio similarity can be captured by public market information such as return covariance. For example, Billio, Getmansky, Lo, and Pelizzon (2012), Neale, Drake, Schorno, and Semann (2012), and Brunetti, Harris, Mankad, and Michailidis (2015) use return covariance as a measure of interconnectedness in the insurance and banking industries. The advantage of using a market-based measure of interconnectedness like return covariance is that it is easy to compute. However, return covariance may not capture the full extent to which insurers are connected through their portfolio strategies. Also some nonbank financial institutions that may contribute to systemic risk also report asset class holdings but do not have market-based measures of interconnectedness readily available (e.g. hedge funds and private banks and insurers). For such institutions, portfolio similarity may be a useful metric to monitor the potential for correlated asset liquidation.[23]

As noted previously, equity returns are only available for public insurer holding companies.

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

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

Although we restrict our analysis in this section to holding companies, the aggregation of insurers to the holding company level accounts for 68-76% of the book value of Schedule D holdings reported by all insurers. The analysis, therefore, applies to the majority of portfolio holdings of the insurance industry.

In order to determine whether the pairwise covariance of stock returns (*RetCov_Pair*) is a good proxy for an insurer pair's portfolio similarity, we include it in an OLS regression of sales similarity as the main independent variable of interest. In Table 9, Model (1) at the asset class level, we find no relationship between *RetCov_Pair* and net sales similarity after adjusting for the pair's portfolio concentration, size, and line of business. In Models (2) and (3), we include portfolio similarity in the set of independent variables and find that it remains statistically significant while the coefficient on *RetCov_Pair* continues to be insignificant.

At the security issuer level, we find that a pair's return covariance is better able to predict the magnitude of net sales. *RetCov_Pair* is significant when portfolio similarity both excluded (Model (5)) or included (Models (6) and (7)). Including portfolio similarity adds power to the specification as the R^2 increases from 36.9% in Model (5) to 42.1% in Model (6). However, the significance is limited to non-PSIFI pairs. We show that return covariance is not a good predictor of the magnitude of common sales of PSIF pairs.[24]

Overall, the findings in this section indicate that market-based measures of interconnectedness, such as the covariance of insurer pair's equity returns, may not fully capture the relationship between similarity in holdings and selling behavior. This is likely due to the fact that equity covariance reflects many different aspects of interconnectedness including the similarity of the insurer pair's balance sheet and operations as well as the similarity of their portfolio allocation strategy. Our results suggest that using return covariance alone to predict the potential for asset liquidation among insurers may be problematic. Next we investigate whether our portfolio similarity measures contain information about future asset liquidation on an individual insurer basis.

[24] This finding is robust even if *Similarity_AC* or *Similarity_I* is not included in the specification.

6 Individual Insurers

In order for regulators to engage in the prudential supervision of systemically important insurers, they must have the ability to identify specific entities that may contribute to the asset liquidation channel of system risk transmission in times of stress. We propose a methodology that transforms the similarity of insurer pairs into a metric of connectedness at the individual insurer level that summarizes an insurer's portfolio similarity with others in the industry. Specifically, we compute the average portfolio similarity of an individual insurer with all other insurers in the sample.

We predict that individual insurers with greater average portfolio similarity will sell more in common with other insurers, i.e., will have a larger aggregate net sales similarity. To test this hypothesis, we construct a measure of aggregate common sales for an insurer as the sum of all its pairwise dollar net sales similarities (*$ Sales Similarity*) with the other insurers in the sample at the asset class or security issuer level. This aggregate dollar sales similarity measure is the dependent variable and is intended to capture an individual insurer's commonality of sales with all other insurers. Our main independent variable of interest is the average portfolio similarity of an insurer with all other insurers in the sample and is similarly constructed at the asset class (*Similarity_AC_Avg*) or security issuer level (*Similarity_I_Avg*).[25]

We also include the following independent variables: *Ln(Total Sales)* defined as the log size of the net sales of insurer i, at both the asset class and security issuer level, business line, the concentration of insurer i's holdings, at the asset class and security issuer level (*Conc*), indicator variables equal to 1 if the insurer is a PSIFI, life insurer or P&C insurer. All independent variables are measured as of the year-end prior to the sales quarter.

The results are presented in Table 10. When examining the effect of insurer characteristics at both the asset class and security issuer level, we show that both the size of the insurer and how much an individual insurer sells is related to the magnitude of its correlated sales with other insurers in the following quarter. Whether an individual insurer is a P&C or life insurer has explanatory power only in specifications (1) and (3). In this case, P&C insurers have lower total sales similarity than other types of insurers. The significance of the P&C indicator in these models but not in

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

Models (2) and (4) is primarily due to the inverse correlation between size and P&C classification. In other words, P&C insurers tend to be smaller than life insurers. We also find that the more concentrated an insurer's portfolio, the greater is its aggregate sales similarity with other insurers.

After controlling for past total sales, business line, and concentration of holdings, we show that an insurer's *Similarity_Avg* can predict its aggregate common sales with all other insurers. In other words, the greater the average similarity in portfolio holdings of a specific insurer, the more it contributes to aggregate common selling.

Interacting a PSIFI indicator with the average portfolio similarity strengthens the relationship between average portfolio similarity and aggregate common net sales. This finding is consistent with the FSOC's concern that larger insurers may contribute more to the asset liquidation channel of systemic risk transmission.

Overall, our results suggest that the average portfolio similarity of an insurer conveys useful additional information even after controlling for other insurer characteristics such as total sales, concentration, and business line. We propose that such a measure could be used by regulators to identify systemically important insurers that are most likely to contribute to asset liquidation vulnerabilities

7 Conclusion

The Financial Stability Oversight Council (FSOC) has the authority to designate nonbank Systemically Important Financial Institutions (SIFIs). Two factors the FSOC currently considers in the designation process are size and interconnectedness between financial companies and these characteristics are assumed to affect the asset liquidation channel. Recent FSOC designations of insurance companies presupposes that larger, systemically risky insurers hold similar assets that could increase financial stability. In this paper, we develop a novel measure of pairwise interconnectedness that focuses on insurance company portfolio similarities and examine its contribution to selling behavior.

Our findings show that pairs of insurers that have greater portfolio similarity will have greater dollar net sales similarity and this result holds across all insurer pairs regardless of SIFI status. Portfolio re-balancing for insurers with similar portfolios is more likely when both insurers are capital constrained with the exception of PSIFIs. We find do not find any differences in the predictability of net sales using portfolios that have been decomposed into liquid and illiquid securities as well as downgraded and non-downgraded security issuers.

We further examine the effect of the similarity in holdings of illiquid and downgraded assets on the predictability of the magnitude of net sales similarity during the financial crisis. We find that greater net selling occurs when portfolios of illiquid and downgraded similarity is higher during the crisis but only for those insurers that are hypothesized to contribute the most to systemic risk, PSIFIs. Thus, our findings provide additional evidence that larger insurers may contribute to the asset liquidation channels of illiquid and credit impaired securities.

In addition, we show that our measure of interconnectedness and its relationship to selling behavior predicts net selling similarity even when incorporating market observable characteristics such as stock return covariance.

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

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

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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 asset-backed and 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 other federal agencies)

Appendix B: Variable Definitions

Variable	Definition
Concentration_AC or Concentration_I	Asset class (_AC) or security issuer(_I) level Herfindahl index of an insurer's portfolio at calendar year end: $Concentration_{i,t} = \sum_{n=1}^{N} w_{i,n,t}^2$ where $w_{i,n,t}$ is asset class/ security issuer n's proportion in insurer i's portfolio at the end of year t. Asset class/ security issuer level proportions are calculated as the dollar amount invested in each asset class/ security issuer relative to the total value of the insurer portfolio.
Crisis	An indicator variable equal to 1 for the years 2007, 2008, and 2009; 0 otherwise.
$ Sales Similarity_AC or $ Sales Similarity_I	The natural logarithm of the dot product of an insurer pair's net dollar sales at the asset class (_AC) or security issuer (_I) level.
Life	An indicator variable equal to 1 if more than 50% of portfolio assets are held by insurance companies in the group that are categorized by A.M. Best as providing life insurance, 0 otherwise.
Life_Pair	An indicator variable equal to 1 if Life=1 for both insurers in a pair, 0 otherwise.
Non-PSIFI	An indicator variable equal to 1 if an insurer (excluding separate accounts) does not meet the $50 billion in assets SIFI designation threshold in any year during our sample period; 0 otherwise.
Non-PSIFI_Pair	An indicator variable equal to 1 if Non-PSIFI=1 for both insurers in a pair, 0 otherwise.
P&C	An indicator variable equal to 1 if more than 50% of portfolio assets are held by insurance companies in the group that are categorized by A.M. Best as providing property and casualty insurance, 0 otherwise.
PC_Pair	An indicator variable equal to 1 if P&C=1 for both insurers in a pair, 0 otherwise.
Post-Crisis	An indicator variable equal to 1 for the years 2010 to 2014, 0 otherwise.
Prod_Conc_AC or Prod_Conc_I	The product of Concentration_AC or Concentration_I for an insurer pair.
Prod_RBC	The natural logarithm of the product of RBC for an insurer pair.
Prod_Size	The natural logarithm of the product of portfolio assets for an insurer pair.
PSIFI	An indicator variable equal to 1 if an insurer could potentially be designated as a SIFI because it has $50 billion or more in assets (excluding those in separate accounts) in at least one year during our sample period; 0 otherwise.
PSIFI_Pair	An indicator variable equal to 1 if PSIFI=1 for both insurers in a pair, 0 otherwise.
RBC	A measure of capital adequacy calculated as the ratio of total adjusted capital to authorized control level risk-based capital (RBC). The RBC ratio at the insurer group level is constructed by (i) calculating the RBC ratio for each company in a group and (ii) computing the group RBC ratio as the weighted average of company RBC ratios using each company's total assets as weights.
RBC _Low_Pair	An indicator variable equal to 1 if RBC is at or below the first quartile of RBC ratio in a given year for both insurers in a pair, 0 otherwise.
RetCov_Pair	The annual return covariance of daily holding-period returns for an insurer pair.
Similarity_AC or Similarity_I	The cosine similarity between a pair of insurers' asset class (_AC) or security issuer (_I) portfolio weights.
Similarity_AC_Avg or Similarity_I_Avg	A simple average of an insurer's portfolio similarities with all other insurers, at the asset class (Similarity_AC) or security issuer (Similarity_I) level.
Similarity_AC_Illiquid	Similarity_AC constructed using only illiquid securities (corporate bonds, municipal bonds, RMBS, CMBS, and ABS).
Similarity_AC_Liquid	Similarity_AC constructed using only liquid securities (equity, mutual fund shares, U.S. government securities, GSE securities, and sovereign bonds).
Similarity_I_Downgraded	Similarity_I constructed using only issuers downgraded to non-investment grade in the following year.
Similarity_I_NotDowngraded	Similarity_I constructed using only issuers not downgraded to non-investment grade in the following year.
Size	The natural logarithm of an insurer's portfolio assets.
Total_Sales_AC or Total_Sales_I	The natural logarithm of an insurer's total net sales at asset class (_AC) or security 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 include groups with small distances among the cluster members with particular statistical distributions. As described in more detail below, we apply internal validation measures, namely *Dunn Index* (Dunn, 1974), *Silhouette Width* (Rousseeuw, 1987) and *Connectivity* (Handl, Knowles, and Kell, 2005), on the most utilized unsupervised clustering algorithms (Self Organizing Maps, Self Organizing Tree Maps, K-means, hierarchical).

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

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

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

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

We run the unsupervised *K-means* algorithm (MacQueen, 1967), yearly, with the following setting:[26]

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

ii) for the following year (Y_t with $t = [2 : 12]$) the centroids obtained by the cluster of the previous year (Y_{t-1}).

The constraint for the cluster number in the first year comes from the outcome of the validation step. The constraint for the centroids' structure of the other years is set to introduce a *short-time*

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

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

We then analyze the clusters looking at:

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

ii) centroids' structure;

iii) transitions of companies among clusters over time.

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

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

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

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

The cluster validation process applied to the yearly dataset provides the best fitting algorithm for the number of clusters. Each validation methodology is applied yearly *kmeans*. A clear indication emerges for the optimal number of clusters being 3 clusters as this appears 21 times over 33 possible outcomes. [27]

Cluster Validation

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

Connectivity (Handl, Knowles, and Kell, 2005) Connectivity measures estimates to what extent the nearest observations (in our case insurers) are placed in the same cluster. We define N as the number of observations in the sample, M the number of attributes of each observation (namely the coordinate of the observation in an M-dimensional space) and $nn_{i(j)}$ the j^{th} nearest

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

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

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

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

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

where L defines the number of neighbor to use.

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

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

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

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

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

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

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

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

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

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

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

Figure 1: Portfolio Composition Through Time

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

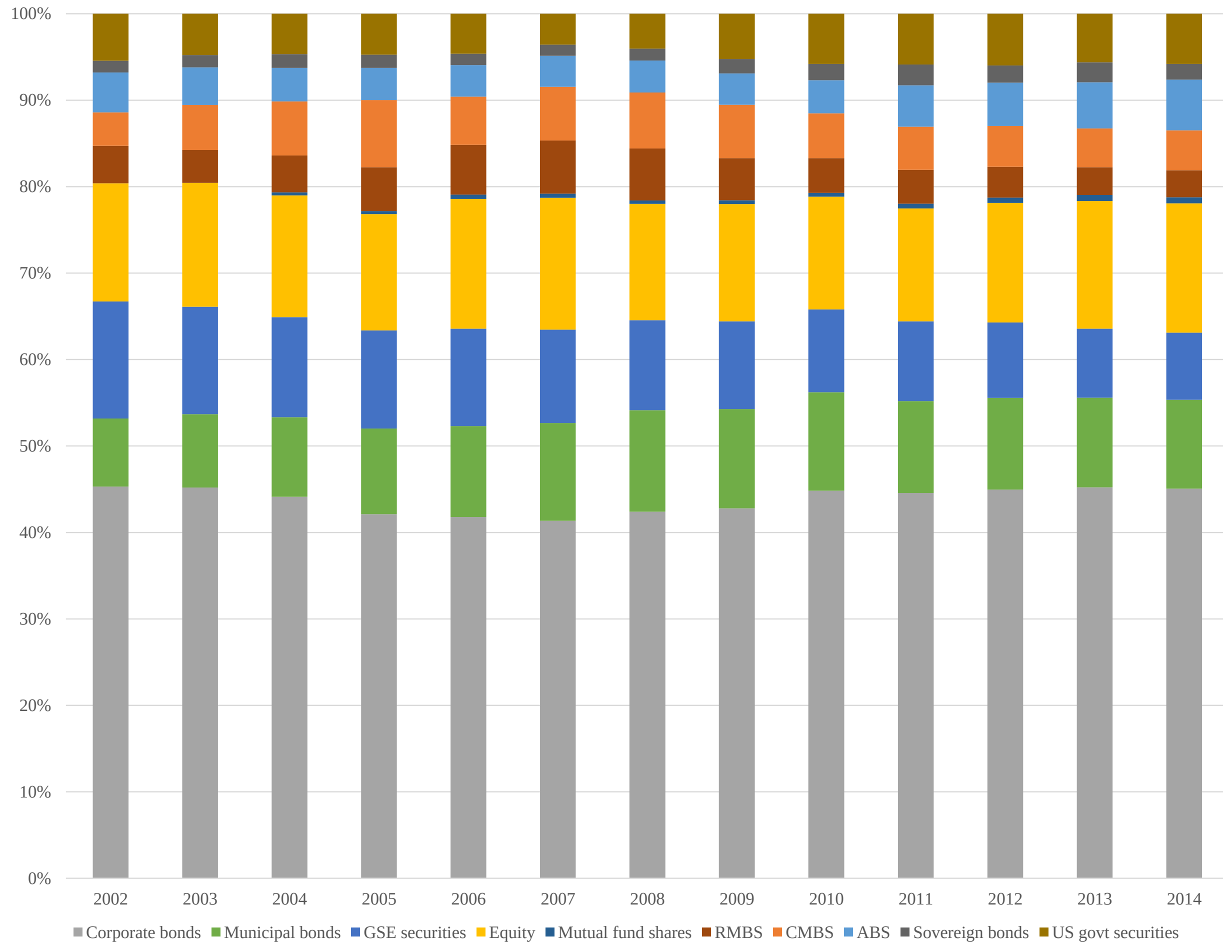


Figure 2: Portfolio Cluster Composition by Primary Asset Classes

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

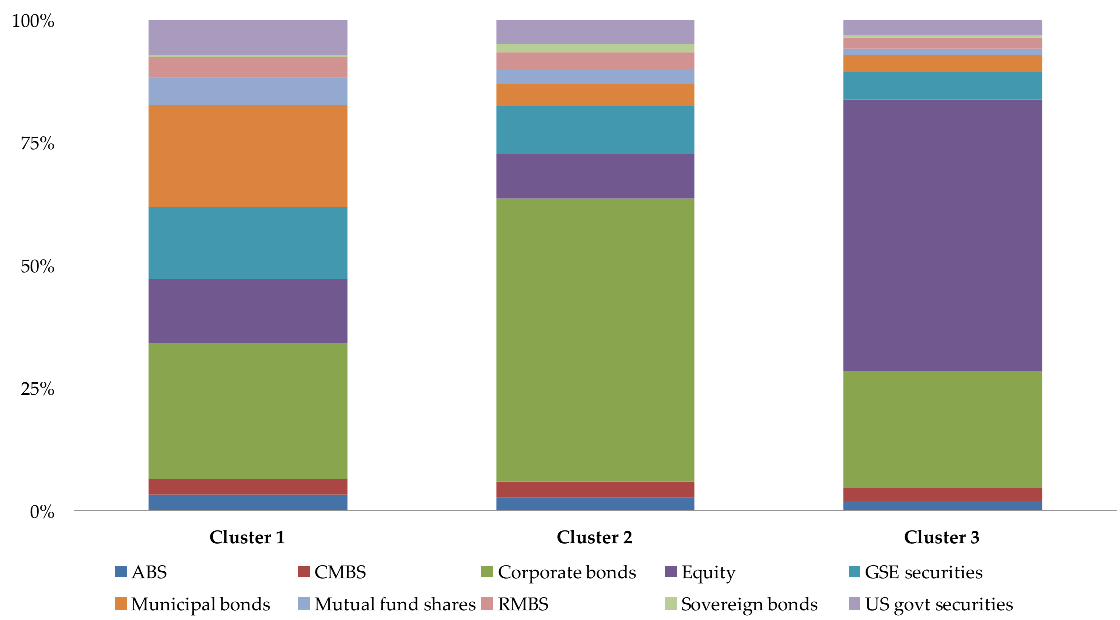
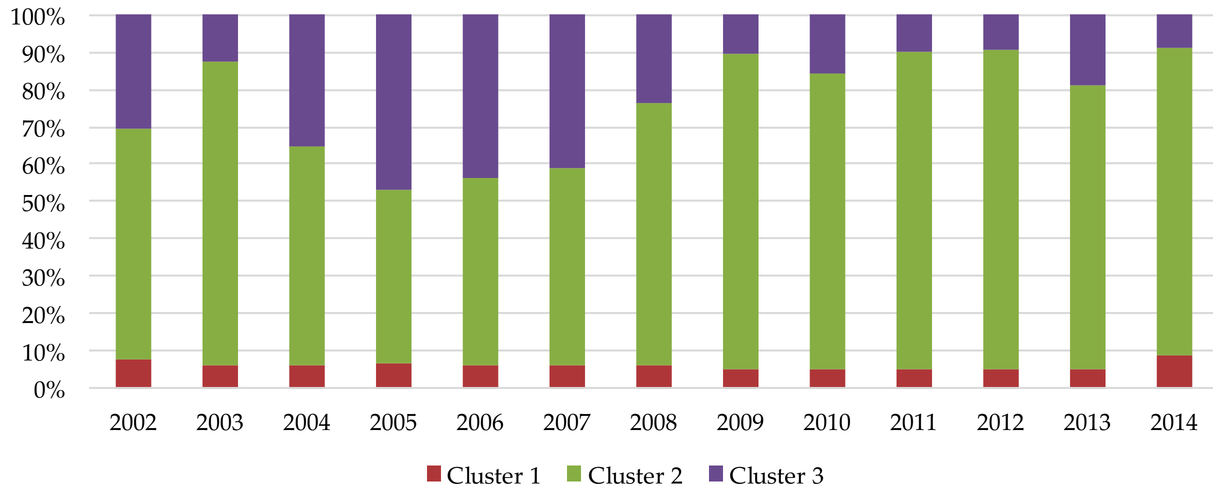
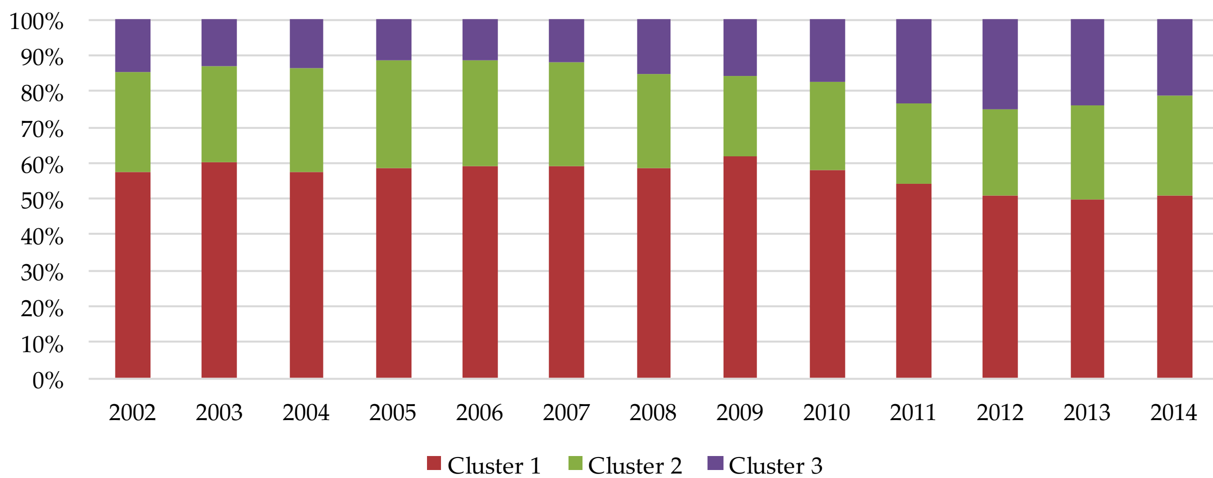


Figure 3: Distribution of PSIFIs and Non-PSIFIs in Portfolio Clusters

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



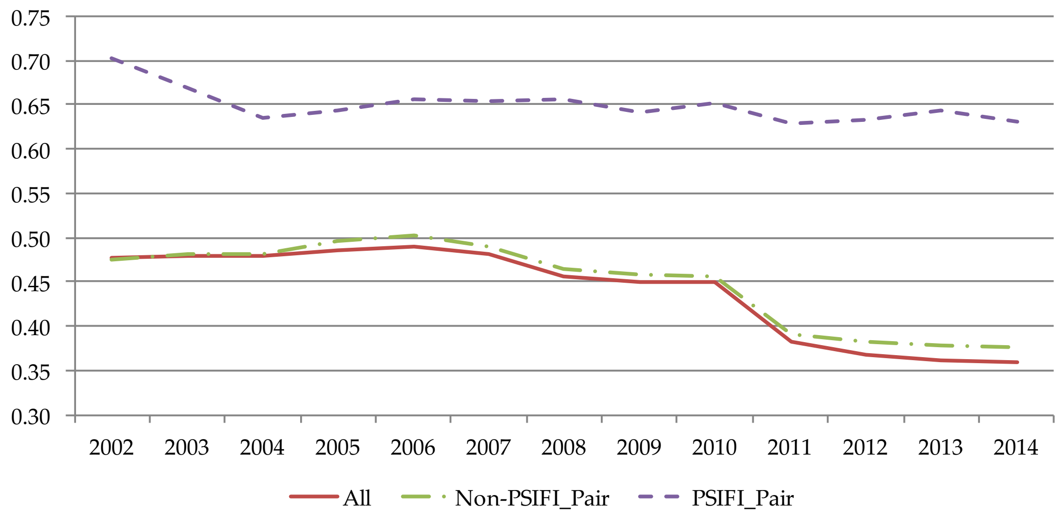
(a) PSIFI



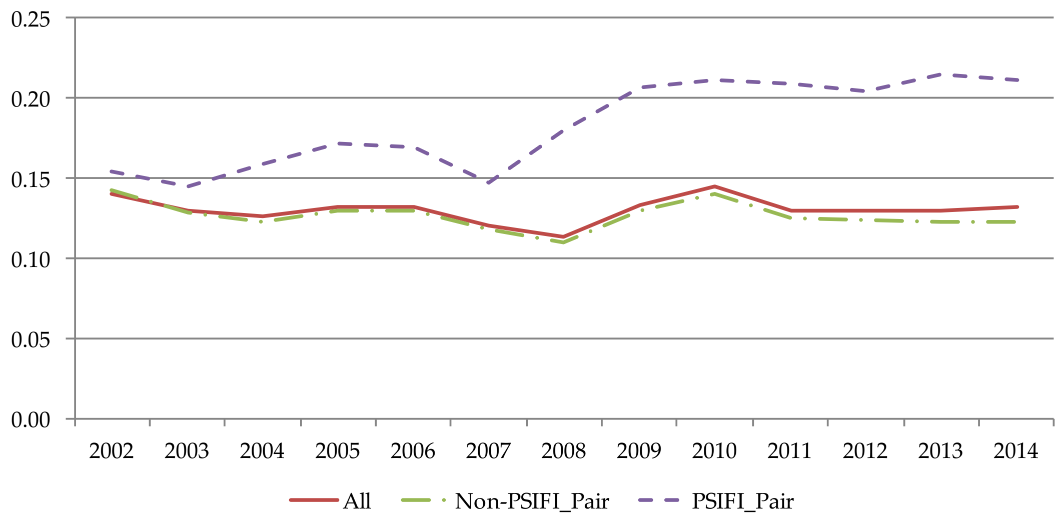
(b) Non-PSIFI

Figure 4: Pairwise Portfolio Similarity Through Time

The figures present the average pairwise portfolio similarity computed at the (a) asset class level ($Similarity\_AC$) and (b) security issuer level ($Similarity\_I$) from 2002 to 2014. The red line represents the average for the sample of all insurers. The violet line represents the average for PSIFI insurers. PSIFI is an insurer that could potentially be designated a SIFI because it have $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. The green line represents the average for non-PSIFI insurers. Non-PSIFI is an insurer that does not meet the PSIFI definition.



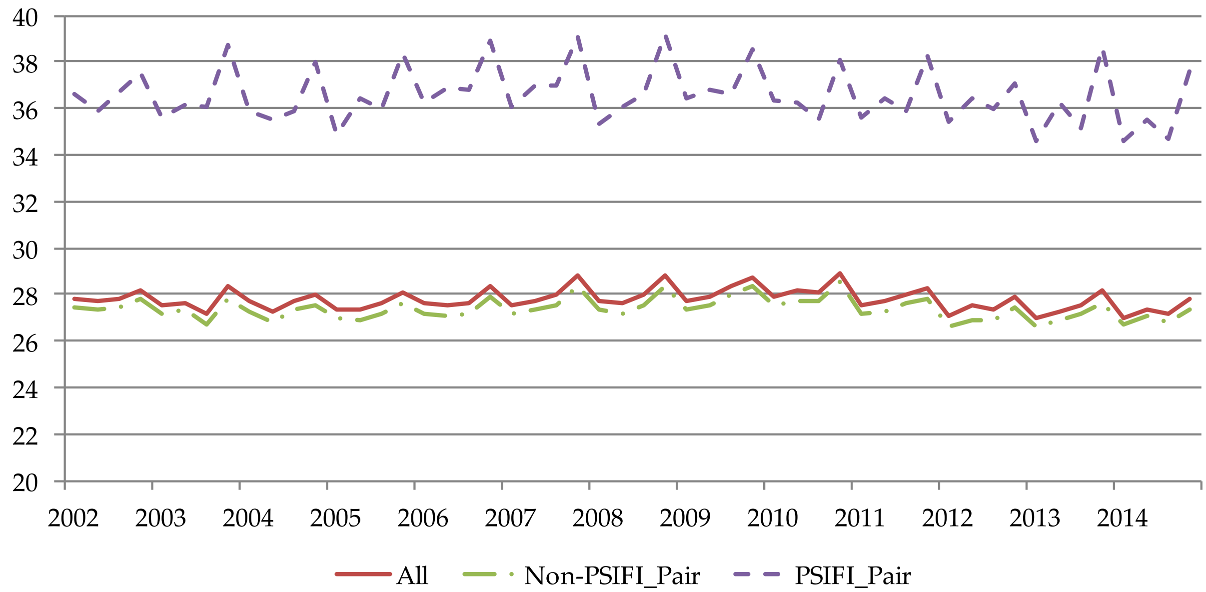
(a) Asset Class Similarity



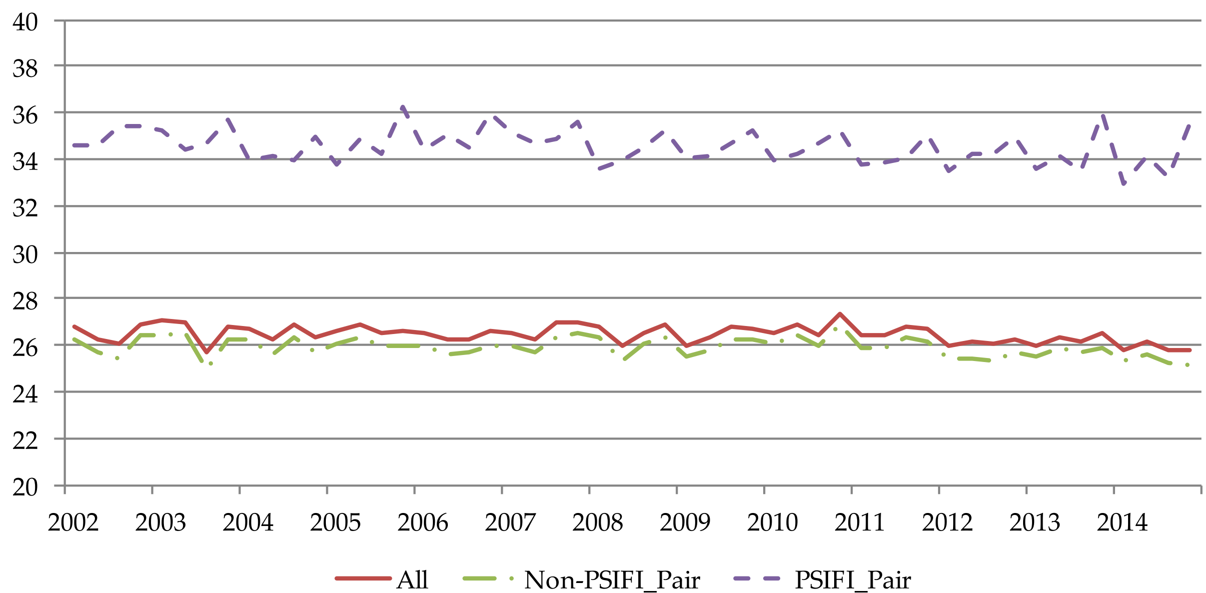
(b) Issuer Similarity

Figure 5: Pairwise Dollar Sales Similarity Through Time

The figures present the average quarterly pairwise dollar net sales similarity computed at the (a) asset class level ($\$SalesSimilarity\_AC$) and (b) security issuer level ($\$SalesSimilarity\_I$) from 2002 to 2014. The red line represents the average for the sample of all insurers. The violet line represents the average for PSIFI insurers. PSIFI is an insurer that could potentially be designated a SIFI because it have $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. The green line represents the average for the non-PSIFI insurers. Non-PSIFI is an insurer that does not meet the PSIFI definition.



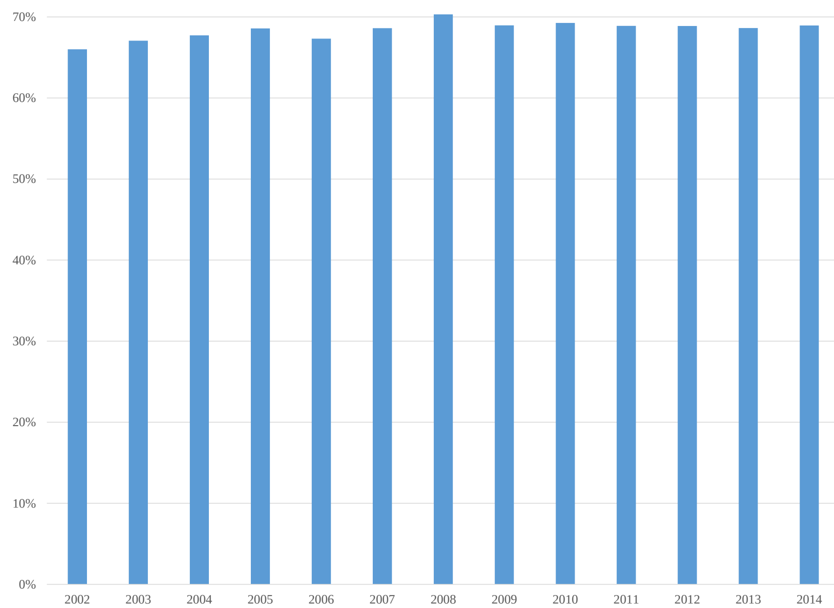
(a) Asset Class $ Sales Similarity



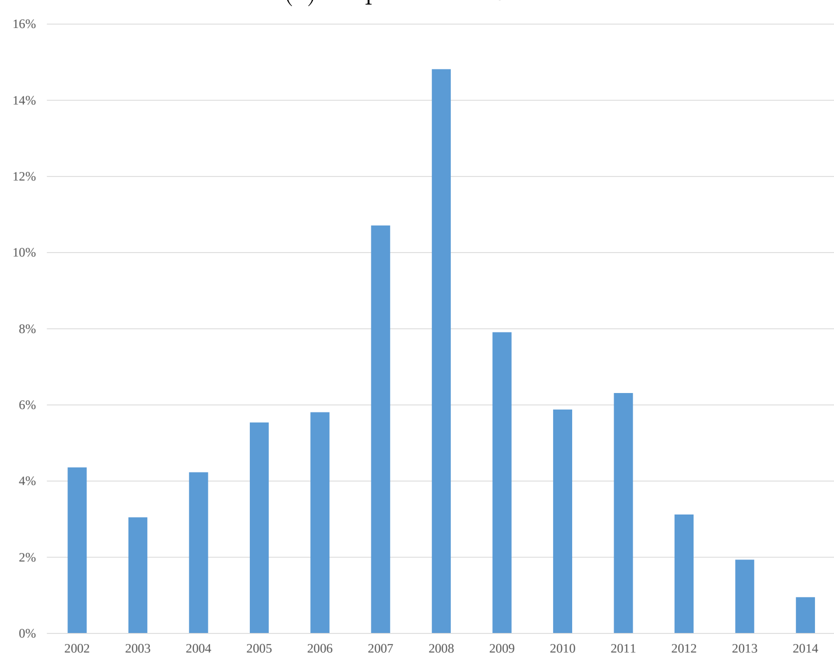
(b) Issuer $ Sales Similarity

Figure 6: Proportion of Illiquid and Downgraded Holdings

The figure presents the proportion of holdings that are composed of (a) illiquid asset classes or (b) downgraded issuers from 2002 to 2014. Illiquid asset classes include corporate bonds, municipal bonds, RMBS, CMBS, and ABS. Downgraded issuers are those downgraded to non-investment garde in the year sold.



(a) Illiquid Asset Classes



(b) Downgraded Issuers

Table 1: Portfolio Composition and Other Insurer Characteristics

The table presents statistics on portfolio composition and other insurer characteristics for all, life, P&C, PSIFI and non-PSIFI insurers from 2002 to 2014. Life insurers operate predominantly in life lines of business. P&C insurers operate predominantly in property and casualty lines of business. *PSIFI* is an insurer that could potentially be designated a SIFI because it have $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. *Non-PSIFI* is an insurer that does not meet the PSIFI definition. *TA* is total assets at calendar year end. Investment portfolio is the dollar value of portfolio holdings disclosed on Schedule D at calendar year end. Corporate bonds, GSE 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 at calendar year end. Number of issues is the number of unique 9-digit CUSIPs in an insurer's portfolio at calendar year end. Number of issuers is the number of unique issuers, identified using 6-digit CUSIPs, in an insurer's portfolio at calendar year end. *Conc_AC* is a Herfindahl index constructed for each insurer in each year as the sum of the squared weights of asset classes in its portfolio. *Conc_I* is a Herfindahl index constructed for each insurer in each year as the sum of the squared weights of issuers in its portfolio. Asset class/ security issuer weights are calculated as the dollar amount invested in each asset class/ security issuer relative to the total value of an insurer's portfolio. Mean, medians and standard deviations are based on the cross-sectional variation of insurers' time series average.

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

Table 2: Summary Statistics for Portfolio Similarity and Dollar Sales Similarity

The table presents summary statistics for portfolio similarity and dollar sales similarity for all, PSIFI and non-PSIFI insurer pairs from 2002 to 2014. PSIFI is an insurer that could potentially be designated a SIFI because it have $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. Non-PSIFI is an insurer that does not meet the PSIFI definition. *Similarity_AC* or *Similarity_I* is asset-class portfolio similarity defined as the cosine similarity between a pair of insurers' asset class or issuer portfolio weights. *Similarity_AC_Liquid* is asset-class portfolio similarity constructed using only liquid securities: equity, mutual fund shares, U.S. government securities, GSE securities, and sovereign bonds. *Similarity_AC_Illiquid* is asset-class portfolio similarity constructed using only illiquid securities: corporate bonds, municipal bonds, RMBS, CMBS, and ABS. *Similarity_I_Downgraded* is security issuer portfolio similarity constructed using only issuers downgraded to non-investment grade in the following year. *Similarity_I_NotDowngraded* is security issuer portfolio similarity constructed using only issuers not downgraded to non-investment grade in the following year. *$ Sales Similarity_AC* or *$ Sales Similarity_I* is the natural logarithm of the dot product of a pair of insurers asset class or security issuer net sales.

	All Pairs					PSIFI Pairs					Non-PSIFI Pairs				
	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
Similarity_AC	0.43	0.28	0.18	0.42	0.65	0.65	0.22	0.51	0.70	0.82	0.44	0.28	0.20	0.44	0.67
Similarity_I	0.13	0.19	0.01	0.05	0.16	0.18	0.15	0.07	0.14	0.26	0.13	0.18	0.01	0.05	0.16
Similarity_AC_Liquid	0.53	0.34	0.21	0.56	0.85	0.66	0.25	0.50	0.71	0.88	0.54	0.34	0.22	0.58	0.86
Similarity_AC_Illiquid	0.47	0.28	0.23	0.48	0.71	0.74	0.21	0.64	0.82	0.90	0.47	0.29	0.23	0.48	0.71
Similarity_I_Downgraded	0.12	0.19	0.00	0.01	0.18	0.41	0.21	0.25	0.43	0.57	0.11	0.19	0.00	0.01	0.16
Similarity_I_NotDowngraded	0.13	0.19	0.01	0.05	0.16	0.18	0.15	0.07	0.13	0.25	0.13	0.18	0.01	0.05	0.16
$ Sales Similarity_AC	27.81	3.97	25.38	27.90	30.42	36.62	3.38	34.88	36.89	38.77	27.43	3.83	25.23	27.61	29.98
$ Sales Similarity_I	26.45	4.09	23.95	26.61	29.14	34.55	3.04	32.99	34.67	36.25	25.94	3.97	23.59	26.19	28.57

Table 3: Determinants of Portfolio Similarity

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

	Portfolio Similarity - Asset Class			Portfolio Similarity - Issuer		
	All Pairs	Non-PSIFI Pairs	PSIFI Pairs	All Pairs	Non-PSIFI Pairs	PSIFI Pairs
	(1)	(2)	(3)	(4)	(5)	(6)
Life_Pair	0.058***	0.051***	0.180***	-0.005***	-0.006***	0.028***
	(8.06)	(6.50)	(21.62)	(-3.51)	(-4.33)	(3.97)
PC_Pair	0.035***	0.033***	0.085***	0.028***	0.028***	0.036**
	(8.20)	(7.42)	(7.31)	(22.10)	(20.34)	(2.33)
PSIFI_Pair	0.086***			0.051***		
	(13.63)			(15.03)		
Non-PSIFI_Pair	0.127***			0.017***		
	(25.68)			(4.65)		
Prod_Size	0.016***	0.015***		0.003***	0.003***	
	(24.51)	(23.30)		(6.01)	(5.72)	
Prod_Conc_AC	-0.333***	-0.330***	-21.496***			
	(-16.71)	(-16.64)	(-9.08)			
Prod_Conc_I				0.579***	0.577***	-112.065***
				(14.63)	(14.69)	(-7.18)
Constant	-0.213***	-0.073***	0.813***	-0.015	0.007	0.145***
	(-9.65)	(-3.06)	(34.65)	(-0.76)	(0.33)	(36.55)
Year FE	Y	Y	Y	Y	Y	Y
N	42,422,256	40,311,016	26,432	42,422,256	40,311,016	26,432
R^2	0.106	0.104	0.429	0.029	0.029	0.066

Table 4: Portfolio Similarity as a Determinant of Dollar Sales Net Similarity

The table presents OLS estimation results for the sample of all, PSIFI and non-PSIFI insurer pairs from 2002 to 2014. The dependent variable is *$ Sales Similarity_AC* or *$ Sales Similarity_I*, which is the natural logarithm of the dot product of a pair of insurers asset class or security issuer net sales. *Similarity_AC* or *Similarity_I* is asset-class portfolio similarity defined as the cosine similarity between a pair of insurers' asset class or security issuer portfolio weights. *Life_Pair* is an indicator variable equal to 1 if both insurers are life insurers, 0 otherwise. *PC_Pair* is an indicator variable equal to 1 if both insurers in a pair are P&C insurers, 0 otherwise. *PSIFI_Pair* is an indicator variable equal to 1 if both insurers in a pair could potentially be designated a SIFI because each has $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period. *Non-PSIFI_Pair* is an indicator variable equal if both insurers in a pair are non-PSIFIs, 0 otherwise. *Prod_Size* is the natural logarithm of the product of portfolio assets for an insurer pair. *Prod_Conc_AC* or *Prod_Conc_I* is the product of the Herfindahl index of an insurer's portfolio at the asset class or issuer level. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	$ Sales Similarity - Asset Class			$ Sales Similarity - Issuer		
	All Pairs	Non-PSIFI Pairs	PSIFI Pairs	All Pairs	Non-PSIFI Pairs	PSIFI Pairs
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC	0.557***	0.508***	1.733***			
	(10.76)	(9.73)	(8.31)			
Similarity_I				4.367***	4.254***	5.750***
				(33.12)	(33.07)	(14.98)
Life_Pair	-0.075**	-0.090**	0.159	0.190***	0.162***	0.594***
	(-2.07)	(-2.26)	(1.14)	(6.05)	(4.71)	(6.57)
PC_Pair	0.218***	0.234***	-0.167	-0.130***	-0.086***	-0.886***
	(7.46)	(7.91)	(-1.18)	(-5.05)	(-3.15)	(-6.72)
PSIFI_Pair	0.673***			0.926***		
	(11.77)			(19.76)		
Non-PSIFI_Pair	-0.113**			0.205***		
	(-2.38)			(5.07)		
Prod_Size	0.749***	0.747***	0.818***	0.732***	0.725***	0.737***
	(100.87)	(103.99)	(12.25)	(82.91)	(85.14)	(14.15)
Prod_Conc_AC	2.390***	2.419***	20.078			
	(5.02)	(5.07)	(1.52)			
Prod_Conc_I				20.069***	19.679***	-86.370
				(14.15)	(14.24)	(-0.30)
Constant	-1.680***	-1.692***	-5.826*	-2.956***	-2.557***	-1.842
	(-6.58)	(-6.66)	(-1.74)	(-8.14)	(-7.42)	(-0.72)
Year-Quarter FE	Y	Y	Y	Y	Y	Y
N	10,130,910	9,145,359	22,460	4,566,178	3,853,888	21,751
R^2	0.458	0.408	0.204	0.432	0.375	0.228

Table 5: Dollar Net Sales Similarity and RBC Ratio

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

	$ Sales Similarity - Asset Class			$ Sales Similarity - Issuer		
	All Pairs	Non-PSIFI Pairs	PSIFI Pairs	All Pairs	Non-PSIFI Pairs	PSIFI Pairs
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC	0.520***	0.463***	1.739***			
	(9.91)	(8.79)	(8.26)			
Similarity_I				4.378***	4.260***	5.747***
				(31.19)	(30.83)	(15.05)
Prod_RBC	-0.022**	-0.018*	-0.010	-0.035***	-0.032**	0.005
	(-2.10)	(-1.77)	(-0.06)	(-2.89)	(-2.49)	(0.04)
RBC_Low_Pair	0.314***	0.297***	1.023	0.418***	0.405***	-0.676
	(6.47)	(6.01)	(1.04)	(8.51)	(8.11)	(-0.51)
Similarity_AC*RBC_Low_Pair	0.200***	0.240***	-0.278			
	(2.86)	(3.35)	(-0.13)			
Similarity_I*RBC_Low_Pair				-0.238	-0.181	9.234
				(-1.47)	(-1.09)	(1.45)
Life_Pair	-0.064*	-0.077*	0.157	0.210***	0.186***	0.592***
	(-1.72)	(-1.87)	(1.13)	(6.59)	(5.31)	(6.47)
PC_Pair	0.210***	0.226***	-0.168	-0.157***	-0.114***	-0.887***
	(6.79)	(7.28)	(-1.19)	(-5.69)	(-3.91)	(-6.55)
PSIFI_Pair	0.697***			0.945***		
	(12.48)			(20.32)		
Non-PSIFI_Pair	-0.154***			0.161***		
	(-3.34)			(4.00)		
Prod_Size	0.743***	0.742***	0.817***	0.727***	0.720***	0.738***
	(95.87)	(98.95)	(11.93)	(81.91)	(83.65)	(14.15)
Prod_Conc_AC	1.907***	1.948***	19.618			
	(3.96)	(4.03)	(1.46)			
Prod_Conc_I				20.808***	20.400***	-90.292
				(11.97)	(12.04)	(-0.29)
Constant	-1.324***	-1.392***	-5.736	-2.575***	-2.220***	-1.912
	(-4.46)	(-4.75)	(-1.59)	(-7.30)	(-6.59)	(-0.72)
Year - Quarter FE	Y	Y	Y	Y	Y	Y
N	9,490,669	8,539,073	22,460	4,335,323	3,643,099	21,751
R^2	0.450	0.397	0.204	0.426	0.366	0.228

Table 6: Dollar Net Sales Similarity, Liquidity and Downgrades by RBC

The table presents OLS estimation results for the sample of all, PSIFI and non-PSIFI insurer pairs from 2002 to 2014. The dependent variable is *\$ Sales Similarity_AC* or *\$ Sales Similarity_I*, which is the natural logarithm of the dot product of a pair of insurers asset class or security issuer net sales. *Similarity_AC_Illiquid* is portfolio similarity constructed using only illiquid securities (Corporate bonds, Municipal bonds, RMBS, CMBS, and ABS). *Similarity_AC_Liquid* is portfolio similiarity constructed using only liquid securities (Equity, Mutual fund shares, US govt securities, GSE securities, and Sovereign bonds). *Similarity_I_Downgraded* is portfolio similarity constructed using only issuers downgraded to non-investment grade in the following year. *Similarity_I_NotDowngraded* is portfolio constructed using only issuers not downgraded to non-investment grade in the following year. *Prod_RBC* is the natural logarithm of the product of RBC (total adjusted capital to authorized control level risk-based capital) for an insurer pair. *RBC _Low_Pair* is an indicator variable equal to 1 if RBC is at or below the first quartile of RBC ratio in a given year for both insurers in a pair, 0 otherwise. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	\$ Sales Similarity - Asset Class			\$ Sales Similarity - Issuer		
	All Pairs	Non-PSIFI Pairs	PSIFI Pairs	All Pairs	Non-PSIFI Pairs	PSIFI Pairs
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC_Illiquid	0.258***	0.203***	1.561***			
	(6.27)	(4.97)	(7.27)			
Similarity_AC_Liquid	0.236***	0.182***	1.146***			
	(4.32)	(3.31)	(5.32)			
Similarity_I_Downgraded				0.913***	0.739***	2.605***
				(9.74)	(7.32)	(10.84)
Similarity_I_NotDowngraded				4.008***	3.927***	3.973***
				(25.04)	(24.90)	(9.34)
RBC_Low_Pair	0.273***	0.233***	1.814	0.486***	0.473***	-0.530
	(4.88)	(4.04)	(1.24)	(8.41)	(7.96)	(-0.38)
Similarity_AC_Illiquid*RBC_Low_Pair	0.097	0.144**	-0.820			
	(1.57)	(2.23)	(-0.18)			
Similarity_AC_Liquid*RBC_Low_Pair	0.155***	0.184***	-0.945			
	(2.87)	(3.40)	(-0.23)			
Similarity_I_Downgraded*RBC_Low_Pair				-0.459***	-0.303***	-4.211
				(-4.04)	(-2.77)	(-1.02)
Similarity_I_NotDowngraded*RBC_Low_Pair				-0.377*	-0.389*	13.314
				(-1.98)	(-2.00)	(1.39)
Prod_RBC	-0.015	-0.010	-0.224	-0.047***	-0.038**	-0.398**
	(-1.17)	(-0.77)	(-1.36)	(-3.24)	(-2.50)	(-2.43)
Life_Pair	-0.069*	-0.082*	0.100	0.195***	0.178***	0.503***
	(-1.90)	(-1.97)	(0.84)	(5.50)	(4.67)	(5.92)
PC_Pair	0.235***	0.252***	-0.172	-0.149***	-0.096***	-0.642***
	(6.85)	(7.22)	(-1.19)	(-5.17)	(-3.07)	(-4.38)
Prod_Size	0.747***	0.746***	0.775***	0.761***	0.757***	0.478***
	(95.94)	(98.67)	(10.87)	(85.61)	(86.16)	(8.04)
PSIFI_Pair	0.694***			0.648***		
	(11.89)			(13.14)		
Non-PSIFI_Pair	-0.110**			0.266***		
	(-2.47)			(6.99)		
Prod_Conc_AC	0.055	0.018	33.191**			
	(0.09)	(0.03)	(2.45)			
Prod_Conc_I				44.407***	43.809***	192.699
				(13.58)	(13.45)	(0.61)
Constant	-1.796***	-1.769***	-4.178	-5.026***	-4.619***	9.904***
	(-5.87)	(-5.83)	(-1.10)	(-12.68)	(-11.83)	(3.08)
Year - Quarter FE	Y	Y	Y	Y	Y	Y
N	9,199,378	8,265,401	22,460	3,655,536	3,028,968	21,748
R^2	0.448	0.394	0.173	0.435	0.372	0.201

Table 7: Dollar Net Sales Similarity, Portfolio Similarity and the Financial Crisis

The table presents OLS estimation results for the sample of all, PSIFI and non-PSIFI insurer pairs from 2002 to 2014. The dependent variable is *$ Sales Similarity_AC* or *$ Sales Similarity_I*, which is the natural logarithm of the dot product of a pair of insurers asset class or security issuer net sales. *Similarity_AC* or *Similarity_I* is asset-class portfolio similarity defined as the cosine similarity between a pair of insurers' asset class or security issuer portfolio weights. *Crisis* is an indicator variable equal to 1 for the years 2007, 2008, and 2009; 0 otherwise. *Post-Crisis* is an indicator variable equal to 1 for the years 2010 to 2014, 0 otherwise. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	$ Sales Similarity - Asset Class			$ Sales Similarity - Issuer		
	All Pairs	Non-PSIFI Pairs	PSIFI Pairs	All Pairs	Non-PSIFI Pairs	PSIFI Pairs
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC	0.427**	0.383**	1.084*			
	(4.57)	(3.50)	(2.36)			
Similarity_I				4.895***	4.812***	7.243***
				(42.38)	(74.23)	(8.87)
Crisis	0.072	0.121	-0.995	0.007	0.092	-0.633**
	(1.23)	(1.67)	(-2.21)	(0.04)	(0.62)	(-3.47)
Similarity_AC*Crisis	0.351*	0.312	1.209			
	(2.88)	(2.32)	(2.26)			
Similarity_I*Crisis				-0.229	-0.330	-0.886
				(-0.91)	(-1.45)	(-1.41)
Post-Crisis	0.103	0.162	-1.713***	-0.040	0.047	-0.789**
	(1.02)	(1.56)	(-36.52)	(-0.43)	(0.53)	(-5.40)
Similarity_AC*Post-Crisis	0.163	0.166	1.024**			
	(1.98)	(1.84)	(3.84)			
Similarity_I*Post-Crisis				-1.004**	-1.005***	-2.990**
				(-5.77)	(-6.69)	(-4.74)
Life_Pair	-0.071	-0.084	0.152	0.206*	0.182*	0.594***
	(-0.83)	(-0.88)	(1.56)	(2.55)	(2.40)	(21.40)
PC_Pair	0.213**	0.228**	-0.180	-0.136*	-0.089	-0.912***
	(3.50)	(3.93)	(-1.72)	(-2.93)	(-1.98)	(-11.15)
Prod_Size	0.749***	0.747***	0.814***	0.732***	0.726***	0.695***
	(49.53)	(52.12)	(6.17)	(53.72)	(54.38)	(8.73)
PSIFI_Pair	0.672**			0.921***		
	(3.79)			(9.71)		
Non-PSIFI_Pair	-0.115			0.200*		
	(-0.81)			(2.87)		
Prod_Conc_AC	2.470***	2.475***	20.879			
	(6.25)	(6.16)	(1.60)			
Prod_Conc_I				20.630***	20.233***	-66.752
				(13.65)	(13.53)	(-0.24)
Constant	-1.994**	-2.030**	-5.365	-3.767***	-3.361**	-1.479
	(-4.25)	(-3.84)	(-0.79)	(-6.80)	(-5.77)	(-0.36)
Quarter FE	Y	Y	Y	Y	Y	Y
N	10,130,910	9,145,359	22,460	4,566,178	3,853,888	21,751
R^2	0.456	0.405	0.184	0.426	0.368	0.212

Table 8: Dollar Net Sales Similarity, Liquidity and Downgrades By Crisis Periods

The dependent variable is *$ Sales Similarity_AC* or *$ Sales Similarity_I*, which is the natural logarithm of the dot product of a pair of insurers asset class or security issuer net sales. *Similarity_AC_Illiquid* is portfolio similarity constructed using only illiquid securities (Corporate bonds, Municipal bonds, RMBS, CMBS, and ABS). *Similarity_AC_Liquid* is portfolio similiarity constructed using only liquid securities (Equity, Mutual fund shares, US govt securities, GSE securities, and Sovereign bonds). *Similarity_I_Downgraded* is portfolio similarity constructed using only issuers downgraded to non-investment grade in the following year. *Similarity_I_NotDowngraded* is portfolio constructed using only issuers not downgraded to non-investment grade in the following year. *Crisis* is an indicator variable equal to 1 for the years 2007, 2008, and 2009; 0 otherwise. *Post-Crisis* is an indicator variable equal to 1 for the years 2010 to 2014, 0 otherwise. The remaining independent variables are defined in Appendix B. All independent variables are measured as of the year-end prior to the sales quarter. Robust t-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	$ Sales Similarity - Asset Class			$ Sales Similarity - Issuer		
	All Pairs	Non-PSIFI Pairs	PSIFI Pairs	All Pairs	Non-PSIFI Pairs	PSIFI Pairs
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity_AC_Illiquid	0.385**	0.340**	0.592**			
	(3.73)	(3.32)	(3.22)			
Similarity_AC_Liquid	0.061	0.035	0.925			
	(1.51)	(0.52)	(2.32)			
Similarity_I_Downgraded				1.214***	1.007***	1.646**
				(14.85)	(8.69)	(4.62)
Similarity_I_NotDowngraded				4.534***	4.456***	6.511***
				(32.48)	(52.51)	(7.38)
Crisis	0.008	0.063	-1.330*	0.060	0.132	-0.886*
	(0.10)	(0.63)	(-2.77)	(0.37)	(0.84)	(-2.76)
Similarity_AC_Illiquid*Crisis	0.023	0.013	1.164*			
	(0.22)	(0.12)	(3.01)			
Similarity_AC_Liquid*Crisis	0.348**	0.316*	0.435			
	(3.79)	(2.76)	(2.08)			
Similarity_I_Downgraded*Crisis				-0.500	-0.452	1.179**
				(-2.09)	(-1.66)	(3.21)
Similarity_I_NotDowngraded*Crisis				-0.212	-0.301	-1.667*
				(-0.66)	(-1.01)	(-2.56)
Post-Crisis	0.097	0.162	-2.142***	0.037	0.108	-0.921**
	(0.96)	(1.53)	(-17.96)	(0.35)	(1.05)	(-4.49)
Similarity_AC_Illiquid*Post-Crisis	-0.277***	-0.287***	2.025***			
	(-5.97)	(-6.10)	(6.07)			
Similarity_AC_Liquid*Post-Crisis	0.313**	0.314**	-0.538			
	(4.89)	(3.68)	(-1.54)			
Similarity_I_Downgraded*Post-Crisis				-0.637**	-0.519*	0.747
				(-3.40)	(-2.35)	(1.39)
Similarity_I_NotDowngraded*Post-Crisis				-1.020***	-1.021***	-3.295**
				(-7.00)	(-9.02)	(-4.32)
Life_Pair	-0.080	-0.094	0.109	0.167	0.149	0.557***
	(-1.00)	(-1.04)	(1.20)	(1.92)	(1.79)	(22.68)
PC_Pair	0.233**	0.248**	-0.142	-0.116	-0.065	-0.801***
	(3.56)	(4.05)	(-1.25)	(-1.88)	(-1.08)	(-8.99)
Prod_Size	0.750***	0.749***	0.838***	0.767***	0.763***	0.614***
	(47.25)	(49.58)	(6.24)	(60.67)	(62.11)	(7.30)
PSIFI_Pair	0.676**			0.633***		
	(3.64)			(6.04)		
Non-PSIFI_Pair	-0.079			0.300**		
	(-0.57)			(3.77)		
Prod_Conc_AC	0.518	0.547	19.804			
	(0.78)	(0.84)	(1.82)			
Prod_Conc_I				48.413***	47.205***	252.119
				(24.58)	(21.50)	(0.93)
Constant	-2.061**	-2.049**	-6.907	-5.540***	-5.096***	1.966
	(-4.26)	(-3.89)	(-0.99)	(-10.67)	(-9.28)	(0.45)
Quarter FE	Y	Y	Y	Y	Y	Y
N	9,763,527	8,799,585	22,460	3,817,877	3,176,186	21,748
R^2	0.455	0.404	0.189	0.441	0.380	0.228

Table 9: Dollar Net Sales Similarity and Return Covariance

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

	$ Sales Similarity - Asset Class				$ Sales Similarity - Issuer			
	All Pairs	All Pairs	Non-PSIFI Pairs	PSIFI Pairs	All Pairs	All Pairs	Non-PSIFI Pairs	PSIFI Pairs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RetCov_Pair	108.143	101.060	82.741	-31.050	74.663***	99.476***	107.380***	7.296
	(1.47)	(1.39)	(0.93)	(-1.31)	(3.91)	(6.09)	(3.54)	(0.27)
Similarity_AC		0.768***	0.756***	1.811***				
		(4.45)	(4.58)	(4.13)				
Similarity_I						6.391***	6.613***	5.720***
						(20.85)	(21.00)	(14.49)
Life_Pair	-0.158*	-0.272***	-0.363***	0.547	0.161**	-0.086	-0.267***	0.927**
	(-1.77)	(-2.69)	(-3.71)	(1.51)	(2.33)	(-1.20)	(-4.00)	(2.26)
PC_Pair	0.392***	0.351***	0.378***	-0.442	-0.316***	0.019	0.101	1.195
	(3.64)	(3.31)	(3.46)	(-0.41)	(-3.09)	(0.21)	(0.95)	(1.59)
Prod_Size	0.754***	0.760***	0.729***	0.928***	0.768***	0.795***	0.718***	1.003***
	(29.44)	(28.67)	(27.12)	(15.97)	(35.75)	(37.83)	(28.91)	(22.16)
PSIFI_Pair	0.677***	0.622***			0.717***	0.604***		
	(7.16)	(6.40)			(10.16)	(8.60)		
Non-PSIFI_Pair	-0.415***	-0.432***			-0.212***	-0.337***		
	(-5.12)	(-5.30)			(-3.66)	(-5.90)		
Prod_Conc_AC	-7.280**	-5.432*	6.533	-11.014***				
	(-2.45)	(-1.99)	(1.62)	(-3.10)				
Prod_Conc_I					170.385***	170.061***	146.673***	-526.345***
					(4.06)	(4.55)	(3.93)	(-3.14)
Constant	-0.914	-1.593	-0.309	-11.625***	-2.867***	-4.865***	-1.576	-15.204***
	(-0.80)	(-1.29)	(-0.26)	(-3.99)	(-2.96)	(-5.05)	(-1.44)	(-7.19)
Year - Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	50,494	50,494	20,133	6,347	40,033	40,033	13,335	6,235
R-squared	0.403	0.404	0.300	0.287	0.369	0.421	0.278	0.339

Table 10: Dollar Net Sales Similarity at the Insurer Level

The table presents OLS estimation results for the sample of insurers from 2002 to 2014. The dependent variable is *$ Sales Similarity_AC* or *$ Sales Similarity_I*, which is the sum of an insurer's pairwise dollar net sales similarity with all other insurers, at the asset class or security issuer level respectively. *$ Sales Similarity_AC* or *$ Sales Similarity_I* is the natural logarithm of the dot product of a pair of insurers asset class or security issuer net sales. *PSIFI* is an indicator variable equal to 1 if an insurer could potentially be designated a SIFI because it have $50 billion or more in assets (excluding those in separate accounts) in at least one year during the sample period, 0 otherwise. *Size* is the natural logarithm of an insurer's portfolio assets. *Total Sales_AC* or *Total Sales_I* is the natural logarithm of an insurer's total net sales at asset class or security issuer level. *Similarity_AC_Avg* or *Similarity_I_Avg* is the simple average of insurer portfolio similarities with all other insurers, at the asset class or security issuer level respectively. *P&C* and *Life* are indicator variables equal to 1 if the insurer is a P&C life insurer respectively, 0 otherwise. *Conc_AC* or *Conc_I* is the concentration of insurer portfolio holdings at the asset class and security issuer level. All independent variables are measured as of the year-end prior to the sales quarter. Robust *t*-statistics are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level respectively.

	$ Sales Similarity - Asset Class		$ Sales Similarity - Issuer	
	All	All	All	All
	(1)	(2)	(3)	(4)
Similarity_AC_Avg	0.472***	0.947***		
	(3.49)	(5.68)		
Similarity_AC_Avg * PSIFI	1.456***	0.640*		
	(3.95)	(1.82)		
Similarity_I_Avg			5.700***	5.391***
			(24.21)	(23.51)
Similarity_I_Avg * PSIFI			2.847***	2.534***
			(4.20)	(3.66)
PSIFI	-0.646***	0.686***	0.064	0.922***
	(-4.02)	(4.39)	(0.62)	(8.67)
Size	0.460***		0.504***	
	(58.22)		(35.26)	
Total Sales_AC	0.317***	0.611***		
	(40.89)	(84.91)		
Total Sales_I			0.462***	0.797***
			(34.20)	(86.90)
P&C	0.046	-0.250***	-0.025	-0.253***
	(1.14)	(-5.48)	(-0.57)	(-5.31)
Life	0.008	0.008	-0.031	-0.012
	(0.16)	(0.15)	(-0.73)	(-0.25)
Conc_AC	0.879***	0.089		
	(7.96)	(0.80)		
Conc_I			2.015***	0.534**
			(8.02)	(2.01)
Constant	13.373***	17.728***	10.184***	14.751***
	(125.46)	(134.53)	(52.09)	(89.38)
Year-Quarter FE	Y	Y	Y	Y
Observations	36,209	36,209	37,719	37,719
R-squared	0.574	0.511	0.545	0.512