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ECONOMETRIC MEASURES OF SYSTEMIC RISK IN THE FINANCE AND INSURANCE
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Econometric Measures of Systemic Risk in the Finance and Insurance Sectors
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ABSTRACT

We propose several econometric measures of systemic risk to capture the interconnectedness among the monthly returns of hedge funds, banks, brokers, and insurance companies based on principal components analysis and Granger-causality tests. We find that all four sectors have become highly interrelated over the past decade, increasing the level of systemic risk in the finance and insurance industries. These measures can also identify and quantify financial crisis periods, and seem to contain predictive power for the current financial crisis. Our results suggest that hedge funds can provide early indications of market dislocation, and systemic risk arises from a complex and dynamic network of relationships among hedge funds, banks, insurance companies, and brokers.

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1 Introduction

The Financial Crisis of 2007–2009 has created renewed interest in systemic risk, a concept originally intended to describe bank runs and currency crises, but which now applies to any broad-based breakdown in the financial system. Systemic risk can be defined as the probability that a series of correlated defaults among financial institutions, occurring over a short time span, will trigger a withdrawal of liquidity and widespread loss of confidence in the financial system as a whole. The events of 2007–2009 have demonstrated that panic and runs can extend to non-bank entities such as money market funds, insurance companies, hedge funds, government-sponsored enterprises, and broker/dealers. Therefore, a precursor to regulatory reform should be the development of formal measures of systemic risk, measures that capture the linkages and vulnerabilities of the entire financial system—not just those of the banking industry. Such measures should be designed to facilitate the monitoring and regulation of the overall level of risk to the system.

In this paper, we propose several econometric measures of systemic risk in the finance and insurance sectors based on the statistical properties of the market returns of hedge funds, banks, brokers, and insurance companies. While the recent financial crisis has illustrated the potential linkages among these four sectors, previous empirical studies have focused only on one or two of them in isolation. Our measures are based on principal components analysis and Granger-causality tests, and motivated by the events that created so much market dislocation in August 1998 and 2007–2009.

For banks, brokers, and insurance companies, we confine our attention to publicly listed entities and use their monthly equity returns in our analysis. For hedge funds—which are private partnerships—we use their monthly reported net-of-fee fund returns. Our emphasis on market returns is motivated by the desire to incorporate the most current information in our systemic risk measures. Market returns reflect information more rapidly than non-market-based measures such as accounting variables. We consider asset- and market-capitalization-weighted return indexes of these four sectors, as well as the individual returns of the 25 largest entities in each sector. While smaller institutions can also contribute to systemic risk,¹ such risks should be most readily observed in the largest entities. We be-

¹For example, in a recent study commissioned by the G-20, the IMF (2009) determined that systemically important institutions are not limited to those that are the largest, but also include others that are highly interconnected and that can impair the normal functioning of financial markets when they fail.

lieve our study is the first to capture the network of causal relationships between the largest financial institutions in these four sectors.

The likelihood of a major dislocation depends on the degree of correlation among the holdings of financial institutions, how sensitive they are to changes in market prices and economic conditions (and the directionality, if any, of those sensitivities, i.e., causality), how concentrated the risks are among those financial institutions, and how closely connected those institutions are with each other and the rest of the economy. The theoretical underpinnings and institutional mechanisms by which these measures combine to produce systemic risk have become clearer.²

Currently, direct information concerning the leverage of and linkages among these financial institutions is largely proprietary and unavailable to any single regulator. Nevertheless, statistical relationships can yield valuable indirect information about the build-up of systemic risk. Moreover, even if regulatory reforms eventually require systemically important entities to provide such information to regulators, the forward-looking nature of equity markets and the dynamics of the hedge-fund industry suggest that an econometric approach may still provide more immediate and actionable measures of systemic risk.

Our focus on hedge funds, banks, brokers, and insurance companies is not random, but motivated by the extensive business ties between them, many of which have emerged only in the last decade. For example, insurance companies have had little to do with hedge funds until recently. However, as they moved more aggressively into non-core activities such as insuring financial products, credit-default swaps, derivatives trading, and investment management, insurers created new business units that competed directly with banks, hedge funds, and broker/dealers. These activities have potential implications for systemic risk when conducted on a large scale (see Geneva Association, 2010). Similarly, the banking industry has been transformed over the last 10 years, not only with the repeal of the Glass-Steagall Act in 1999, but also through financial innovations like securitization that have blurred the distinction between loans, bank deposits, securities, and trading strategies. The types of business relationships between these sectors have also changed, with banks and insurers providing credit to hedge funds but also competing against them through their own proprietary trading desks, and hedge funds using insurers to provide principal protection on their

²See, for example Acharya and Richardson (2009), Allen and Gale (1994, 1998, 2000), Battiston et al. (2009), Brunnermeier (2009), Brunnermeier and Pedersen (2009), Gray (2009), Rajan (2006), Danielsson, Shin, and Zigrand (2009), and Reinhart and Rogoff (2009).

funds while simultaneously competing with them by offering capital-market-intermediated insurance such as catastrophe-linked bonds.

Our empirical findings show that liquidity and connectivity within and across all four sectors are highly dynamic over the past decade, varying in quantifiable ways over time and as a function of market conditions. Specifically, we find that over time, all four sectors have become highly interrelated and less liquid, increasing the level of systemic risk in the finance and insurance industries prior to crisis periods. These patterns are all the more striking in light of the fact that our analysis is based on monthly returns data. In a framework where all markets clear and past information is fully impounded into current prices, we should not be able to detect significant statistical relationships on a monthly timescale.

Moreover, our principal components estimates and Granger-causality tests point to an important asymmetry in the connections: the returns of banks and insurers seem to have more significant impact on the returns of hedge funds and brokers than vice versa. We also find that this asymmetry became highly significant prior to the Financial Crisis of 2007–2009, indicating that our measures may be useful as early warning indicators of systemic risk. This pattern suggests that banks may be more central to systemic risk than the so-called “shadow banking system” (the non-bank financial institutions that engage in banking functions). By competing with other financial institutions in non-traditional businesses, banks and insurers may have taken on risks more appropriate for hedge funds, leading to the emergence of a “shadow hedge-fund system” in which systemic risks could not be managed by traditional regulatory instruments. Another possible interpretation is that, because they are more highly regulated, banks and insurers are more sensitive to Value-at-Risk changes through their capital requirements (Basel II and Solvency II), hence their behavior may generate endogenous feedback loops with perverse spillover effects to other financial institutions.

In Section 2 we provide a brief review of the literature on systemic risk measurement, and describe our proposed measures in Section 3. The data used in our analysis is summarized in Section 4, and the empirical results and robustness checks are reported in Sections 5 and 6, respectively. We conclude in Section 7.

2 Literature Review

De Bandt and Hartmann (2000), who undertook a thorough survey of the systemic risk literature, provide the following definitions for systemic risk and crises:

A systemic crisis can be defined as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system. While the “special” character of banks plays a major role, we stress that systemic risk goes beyond the traditional view of single banks’ vulnerability to depositor runs. At the heart of the concept is the notion of “contagion”, a particularly strong propagation of failures from one institution, market or system to another.

In a recent paper, Brunnermeier et al. (2009) describe requirements for a systemic risk measure: “A systemic risk measure should identify the risk on the system by individually systemic institutions, which are so interconnected and large that they can cause negative risk spillover effects on others, as well as by institutions which are systemic as part of a herd.”

In this paper we use these definitions to analyze systemic risk. Our analysis concentrates on the interconnectedness of all major financial institutions: banks, brokers, insurance companies, and hedge funds. Allen (2001) underlined the importance of mapping out relationships between financial institutions when studying financial fragility and systemic risk. The theoretical framework underlying our analysis refers to interlinkages among financial institutions that could spread both through negative externalities or fundamental shocks, as well as liquidity, volatility spirals, or network effects. The channels through which these spirals can spread are many and well described in the literature, beginning with Bhattacharya and Gale (1987), Allen and Gale (1998, 2000), Diamond and Rajan (2005), and more recently by Brunnermeier and Pedersen (2009), Brunnermeier (2009), Danielsson and Zigrand (2008), Danielsson, Shin, and Zigrand (2009), Battiston et al. (2009), and Castiglionesi, Periozzi, and Lorenzoni (2009) among others.

The empirical literature on systemic risk can be loosely divided into three groups. The first group involves bank contagion, and is mostly based on the autocorrelation of the number of bank defaults, bank returns, and fund withdrawals, as well as exposures among operating banks in which a default by one bank would render other banks insolvent (examples of these studies are cited in De Bandt and Hartmann, 2000). More recently, Lehar (2005) estimated correlations between bank-asset portfolios and used default probabilities of financial institutions as a measure of systemic risk. Jorion (2005) analyzed similarities in bank trading risk, and Bartram, Brown, and Hund (2007) used cumulative negative abnormal returns, maximum-likelihood estimation of bank failure probabilities implied by equity prices, and

estimates of systemic risk implied by equity option prices to measure the probability of systemic failure.

In the wake of the Subprime Mortgage Crisis of 2007, the Bank of England study (Aikman et al., 2009) investigated funding-liquidity risk by integrating balance-sheet-based models of credit and market risk with a network model to evaluate the probability of bank default. Huang, Zhou, and Zhou (2009) proposed a measure of systemic risk based on the price of insuring twelve major U.S. banks against financial distress using ex-ante bank default probabilities and forecasted asset-return correlations.

The second group of empirical studies of systemic risk involves banking crises, aggregate fluctuations, and lending booms. These studies focus on bank capital ratios and bank liabilities, and show that aggregate variables such as macroeconomic fundamentals contain significant predictive power, providing evidence in favor of the macro perspective on systemic risk in the banking sector (Gorton, 1988; Gonzalez-Hermosillo, Pazarbasioglu, and Billings, 1997; and Gonzalez-Hermosillo, 1999). In a more recent study, Bhansali, Gingrich and Longstaff (2008) used the prices of indexed credit derivatives to extract market expectations about the nature and magnitude of credit risk in financial markets. The authors extracted the “systemic credit risk” component from index credit derivatives. They found that systemic risk during the 2007–2009 Financial Crisis is double that of the May 2005 GM credit-downgrade event. De Nicoló and Lucchetta (2009) investigated the impact and transmission of structurally identifiable shocks within and between the macroeconomy, financial markets, and intermediaries, as well as their “tail” realizations.

The third group of studies in the empirical systemic risk literature focuses on contagion, spillover effects, and joint crashes in financial markets. These studies are based on simple correlation, correlation derived from ARCH models, extreme dependence of securities market returns, and securities market co-movements not explained by fundamentals. They involve mainly currency and financial crises observed in the second half of the 1980’s and 1990’s. Examples include Kaminsky and Reinhart (1998, 2000), who used a simple vector autoregression model to run Granger-causality tests between the interest and exchange rates of five Asian economies before and after the Asian crisis. The authors did not detect any Granger-causal relations before the Asian crisis, but many were detected during and after the crisis. Forbes and Rigobon (2001) proposed a measure of correlation to correct for the bias stemming from changes in volatility in contagion detection, and applied this measure

to the Asian Crisis.

The first study of extreme dependence was conducted by Mandelbrot (1963), and subsequently revisited by Jansen and de Vries (1991) and Longin (1996) to measure the tail behavior (booms and crashes) of stock market returns. Longin and Solnik (2001) use extreme value theory to show that the correlation of large negative returns is much larger than the correlation of positive returns. Bae, Karolyi, and Stulz (2003) introduced a new approach to evaluate contagion in financial markets based on the coincidence of extreme-return shocks across countries within a region and across regions. Boyson, Stahel, and Stulz (2009) used quantile regression and logit models to analyze co-movement among hedge-fund strategies, and found strong evidence of contagion among these hedge-fund strategies. Quantile regression methods have also been used by Adrian and Brunnermeier (2009) in their CoVaR measure of systemic risk. Recently, a set of measures based on rare and unknown outcomes and information entropy has been proposed by Duggey (2009). Gray and Jobst (2010) proposed measuring systemic risk via contingent claims analysis. Kritzman, Li, Page, and Rigobon (2010) introduced a systemic risk measure called the absorption ratio based on principal components analysis. And Acharya, Pedersen, Philippon, and Richardson (2010) have proposed “systemic expected shortfall” (SES) as a measure of a financial institution’s propensity to be undercapitalized when the system as a whole is undercapitalized, which can be used to measure each financial institution’s contribution to systemic crisis.

Our approach—to measure the degree of connectivity among financial institutions and how the risk profiles of these institutions can generate systemic risk—is complementary to these studies. In particular, motivated by De Bandt and Hartmann (2000), Brunnermeier et al. (2009) among others, we take a broader perspective by defining the *system* of major players as hedge funds, brokers, banks, and insurers. For example, Chan et al. (2006) found that funding relationships between hedge funds and large banks that have brokerage divisions contribute to systemic risk. Fung and Hsieh (2002, 2004) and Chan et al. (2006) showed that hedge-fund returns are nonlinearly related to equity market risk, credit risk, interest rate risk, exchange rate risk, and option-based factors. Brunnermeier (2009) argued that hedge funds can be commonly affected by financial crises through many mechanisms: funding liquidity, market liquidity, loss and margin spirals, runs on hedge funds, and aversion to Knightian uncertainty. The importance of brokers and insurers have been underscored by the current financial crisis. In particular, the role of funding risk and the interconnectedness of

brokers and hedge funds has been considered recently by King and Maier (2009), Aragon and Strahan (2009), Brunnermeier and Petersen (2009), and Klaus and Rzepkowski (2009). The Basel Committee on Banking Supervision (2009) emphasized that the interconnectedness of large financial institutions transmitted negative shocks across the financial system and the economy in the Financial Crisis of 2007–2009.

Our work is also related to Boyson, Stahel, and Stulz (2009) who investigated contagion from lagged bank- and broker-returns to hedge-fund returns. We investigate these relationships as well, but also consider the possibility of reverse contagion, i.e., causal effects from hedge funds to banks and brokers. Moreover, we add a fourth sector—insurance companies—to the mix, which has become increasingly important, particularly during the most recent financial crisis.

Our analysis is also complementary to the CoVaR analysis of Adrian and Brunnermeier (2009), in which four groups of financial institutions—brokers, banks, real estate institutions, and insurance companies—are analyzed using daily data. CoVaR is an alternate measure of systemic risk that captures the value at risk (VaR) of financial institutions conditional on other institutions being in distress. We add to this line of inquiry by estimating causal relationships between financial institutions and by also incorporating hedge funds, an important sector of the financial system.

Finally, our paper is complementary to Acharya, Pedersen, Philippon, and Richardson (2010) who measure each bank’s contribution to systemic risk and suggest ways to limit it through taxes and regulation. In contrast, our analysis is not meant to be directly applicable to determining optimal bank capital requirements or taxation policy, but may serve instead as early warning signals of potential market dislocation, and may also be used to detect systemically important institutions and linkages.

3 Systemic Risk Measures

In this section we summarize our measures of systemic risk, which are designed to capture changes in correlation and causality among financial institutions. In Section 3.1, we propose principal components analysis as a means of capturing increased correlation, and Section 3.2 contains a description of the Granger-causality tests we use to determine the directionality of correlation.

3.1 Principal Components Analysis

Increased commonality among the asset returns of banks, brokers, insurers, and hedge funds can be empirically detected by using principal components analysis (PCA) to decompose the covariance matrix of the four index returns (see Muirhead, 1982 for an exposition of PCA). If, for example, asset returns are driven by a linear K -factor model, the first K principal components should explain most of the time-series variation in returns. More formally, if

$$R_{jt} = \alpha_j + \delta_1 F_{1t} + \cdots + \delta_K F_{Kt} + \epsilon_{jt} \quad (1)$$

where $E[\epsilon_{jt}\epsilon_{j't}] = 0$ for any $j \neq j'$, then the covariance matrix Σ of the vector of returns $\mathbf{R}_t \equiv [R_{1t} \ \cdots \ R_{Jt}]'$ can be expressed as

$$\text{Var}[\mathbf{R}_t] \equiv \Sigma = \mathbf{Q}\Theta\mathbf{Q}' \quad , \quad \Theta = \begin{bmatrix} \theta_1 & 0 & \cdots & 0 \\ 0 & \theta_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & 0 & \theta_N \end{bmatrix} \quad (2)$$

where Θ contains the eigenvalues of Σ along its diagonal and \mathbf{Q} is the matrix of corresponding eigenvectors. Since Σ is a covariance matrix, it is positive semidefinite hence all the eigenvalues are nonnegative. When normalized to sum to one, each eigenvalue can be interpreted as the fraction of the total variance of turnover attributable to the corresponding principal component. If (1) holds, it can be shown that as the size N of the cross section increases without bound, exactly K normalized eigenvalues of Σ approach positive finite limits, and the remaining $N - K$ eigenvalues approach 0 (see, for example, Chamberlain, 1983, and Chamberlain and Rothschild, 1983). Therefore, the plausibility of (1), and the value of K , can be gauged by examining the magnitudes of the eigenvalues of Σ .

The only challenge is the fact that the covariance matrix Σ must be estimated, hence we encounter the well-known problem that the standard estimator

$$\hat{\Sigma} \equiv \frac{1}{T - J} \sum_{t=1}^T (\mathbf{R}_t - \bar{\mathbf{R}})(\mathbf{R}_t - \bar{\mathbf{R}})'$$

is singular if the number of assets J in the cross section is larger than the number of time series observations T . Therefore, we limit our attention to the index returns of banks, brokers,

insurers, and hedge funds to maximize the number of degrees of freedom.³ By examining the time variation in the magnitudes of the eigenvalues of index returns’ covariance matrix, we may be able to detect increasing correlation among the four financial sectors, i.e., increased connections and integration as well as similarities in risk exposures, which can contribute to systemic risk.

3.2 Granger Causality Tests

To investigate the dynamic propagation of systemic risk, it is important to measure not only the degree of interconnectedness between financial institutions, but also the direction of the relationship. One econometric measure is Granger causality, a statistical notion of causality based on forecast power. X is said to “Granger-cause” Y if past values of X contain information that helps predict Y above and beyond the information contained in past values of Y alone. The mathematical formulation of this test is based on linear regressions of Y on X and X on Y , and its application to our framework is described in the Appendix.

In an informationally efficient market, price changes should not be related to other lagged variables, hence a Granger-causality test should not detect any causality. However, in presence of Value-at-Risk constraints or other market frictions such as transactions costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on shortsales, we may find Granger causality among price changes of financial assets. Moreover, this potential “forecastability” cannot easily be “arbitraged” away, precisely because of the presence of these frictions. From this perspective, the degree of Granger causality in asset returns can be viewed as a proxy for the spillover among market participants as suggested by Danielsson, Shin, and Zigrand (2009) and Battiston et al. (2009). As this effect is amplified, the tighter are the connections and integration among financial institutions, heightening the severity of systemic events as shown by Castiglionesi, Periozzi, and Lorenzoni (2009) and Battiston et al. (2009).

The standard Granger-causality measure is linear, and cannot capture nonlinear and higher-order causal relationships. This limitation is potentially relevant for our purposes since we are interested in whether an increase in riskiness (e.g., volatility) in one financial

³Singularity by itself does not pose any problems for the computation of eigenvalues—this follows from the singular-value decomposition theorem—but it does have implications for the statistical properties of estimated eigenvalues. For example, Lo and Wang (2000) report Monte Carlo evidence that the eigenvalues of a singular estimator of a positive-definite covariance matrix can be severely biased.

institution leads to an increase in the riskiness of another. To capture these higher-order effects, we also consider a second causality measure that we call “nonlinear Granger causality”, which is based on Markov-chain models of returns. This extension of linear Granger causality can capture the effect of one financial institution’s return on the future mean and variance of the returns of another financial institution, which should be able to detect the volatility-based interconnectedness hypothesized by Danielsson, Shin, and Zigrand (2009).

More formally, consider the case of hedge funds and banks, and let ZH_t and ZB_t be Markov chains that characterize the expected returns and volatilities of the two indexes, respectively, i.e.:

$$R_{j,t} = \mu(Z_{j,t}) + \sigma(Z_{j,t})u_{j,t} \quad (3)$$

where $R_{j,t}$ is the excess return of index j in period t , $j = H, B$, $u_{j,t}$ is independently and identically distributed (IID) over time, and $Z_{j,t}$ is a two-state Markov chain with transition probability matrix $\mathbf{P}_{z,j}$ for index j .

We can test the nonlinear causal interdependence between these two series by testing the following hypotheses (the general case of nonlinear Granger-causality estimation is considered in the Appendix):

1. Causality from ZH_t to ZB_t
2. Causality from ZB_t to ZH_t

The joint process $Y_t \equiv (ZH_t, ZB_t)$ is itself a first-order Markov chain with transition probabilities:

$$P(Y_t | Y_{t-1}) = P(ZH_t, ZB_t | ZH_{t-1}, ZB_{t-1}) . \quad (4)$$

where all the information from the past history of the process which is relevant for the transition probabilities at time t is represented by the previous state of the process, i.e. regimes at time $t-1$. Under the additional assumption that the transition probabilities do not vary over time, the process can be defined as a Markov chain with stationary transition probabilities, summarized in the transition matrix \mathbf{P} . We can then decompose the joint

transition probabilities as:

$$P(Y_t|Y_{t-1}) = P(ZH_t, ZB_t | ZH_{t-1}, ZB_{t-1}) \quad (5)$$

$$= P(ZB_t | ZH_t, ZH_{t-1}, ZB_{t-1}) \times P(ZH_t | ZH_{t-1}, ZB_{t-1}) . \quad (6)$$

According to this decomposition and following Billio and Di Sanzo (2009) we run the following two tests of nonlinear Granger causality:

1. Granger Non-Causality from ZH_t to ZB_t :

$$H_{ZH \Rightarrow ZB} \quad (ZH_t \not\Rightarrow ZB_t)$$

by decomposing the joint probability:

$$P(ZH_t, ZB_t | ZH_{t-1}, ZB_{t-1}) = P(ZH_t | ZB_t, ZH_{t-1}, ZB_{t-1}) \times P(ZB_t | ZH_{t-1}, ZB_{t-1}) . \quad (7)$$

In this case, the last term becomes

$$P(ZB_t | ZH_{t-1}, ZB_{t-1}) = P(ZB_t | ZB_{t-1}) .$$

2. Granger Non-Causality from ZB_t to ZH_t :

$$H_{ZB \Rightarrow ZH} \quad (ZB_t \not\Rightarrow ZH_t)$$

by requiring that ZB_{t-1} does not appear as a second term of the previous decomposition, thus

$$P(ZH_t | ZH_{t-1}, ZB_{t-1}) = P(ZH_t | ZH_{t-1}) .$$

4 The Data

For the main analysis, we use monthly returns data for hedge funds, brokers, banks, and insurers, described in more detail in Sections 4.1 and 4.2. Summary statistics are provided in Section 4.3.

4.1 Hedge Funds

Our hedge-fund data consists of aggregate hedge-fund index returns from the CS/Tremont database from January 1994 to December 2008, which are asset-weighted indexes of funds with a minimum of \$10 million in assets under management, a minimum one-year track record, and current audited financial statements. The following strategies are included in the total aggregate index (hereafter, known as “Hedge Funds”): Dedicated Short Bias, Long/Short Equity, Emerging Markets, Distressed, Event Driven, Equity Market Neutral, Convertible Bond Arbitrage, Fixed Income Arbitrage, Multi-Strategy, and Managed Futures. The strategy indexes are computed and rebalanced monthly and the universe of funds is redefined on a quarterly basis. We use net-of-fee monthly excess returns. This database accounts for survivorship bias in hedge funds (Fung and Hsieh, 2000).

We also use individual hedge-fund data from the TASS Tremont database. Funds in the TASS Tremont database are similar to the ones used in the CS/Tremont indexes, however, TASS Tremont does not implement any restrictions on size, track record, or the presence of audited financial statements. Therefore, the TASS Tremont database contains more funds—a total of 8,770 hedge funds in both Live and Defunct databases—than its corresponding index.

4.2 Banks, Brokers, and Insurers

Data for individual brokers is obtained from the University of Chicago’s Center for Research in Security Prices Database, from which we select the monthly returns of all companies with SIC Codes from 6200 to 6299 and construct our value-weighted broker index (hereafter, called “Brokers”). Indexes for “Banks” and “Insurers” are constructed similarly using SIC codes 6000–6199 for banks and 6300–6499 for insurers.

4.3 Summary Statistics

Table 1 reports the sample size, annualized mean, annualized standard deviation, minimum, maximum, median, skewness, kurtosis, first three autocorrelation coefficients ρ_1 , ρ_2 , and ρ_3 , and corresponding p -values for our dataset. Brokers have the highest annual mean of 14.22% and the highest standard deviation of 29.05%. Insurers have the lowest mean, 7.90%, but a relatively high standard deviation of 17.84%. Hedge Funds have the highest autocorrelation of 0.22, which is particularly striking when compared to those of Banks (0.02), Insurers

(0.08), and Brokers (0.13). This finding is consistent with the hedge-fund industry’s higher exposure to illiquid assets and return-smoothing (see Getmansky, Lo, and Makarov, 2004).

Statistic	Hedge Funds	Brokers	Banks	Insurers	S&P500
Sample Size	180	180	180	180	180
Ann. Mean (%)	8.72	14.22	10.12	7.90	8.59
Ann. SD (%)	7.96	29.05	19.37	17.84	15.17
Min (%)	-7.55	-31.56	-22.38	-24.09	-16.64
Max (%)	8.53	26.75	14.26	23.67	9.84
Median (%)	0.79	1.64	1.40	0.97	1.26
Skewness	-0.17	-0.41	-0.94	-0.47	-0.75
Kurtosis	5.26	3.99	5.64	7.56	4.27
ρ_1	0.22	0.13	0.02	0.08	0.10
p-value(ρ_1)	0.00	0.07	0.80	0.30	0.17
ρ_2	0.11	-0.09	-0.01	0.02	-0.01
p-value(ρ_2)	0.13	0.22	0.88	0.80	0.90
ρ_3	0.04	0.03	-0.01	-0.05	0.07
p-value(ρ_3)	0.61	0.73	0.93	0.54	0.35

Table 1: Summary statistics for monthly CS/Tremont Hedge Fund index returns, value-weighted return indexes for Banks, Brokers, Insurers, and S&P 500 returns from January 1994 to December 2008.

5 Empirical Analysis

In this section, we implement the measures defined in Section 3 using historical data for index returns corresponding to the four sectors of the finance and insurance industries described in Section 4. Section 5.1 contains the results of principal components analysis applied to the return indexes, and Section 5.2 reports the outcomes of linear and nonlinear Granger-causality tests. To better understand the implications of these Granger-causality relationships, in Section 5.3 we present results for individual financial institutions and simple visualizations via network diagrams. And in Section 5.4, we evaluate the predictive power of Granger causality relationships.

5.1 Principal Components Analysis

Since the heart of systemic risk is commonality among multiple institutions, we attempt to measure commonality through Principal Components Analysis (PCA) applied to the collection of indexes we constructed in Section 4 over the whole sample period, 1994–2008. The

time-series results for eigenvalues and eigenvector exposures are presented in Figures 1 and 2.

In addition, we tabulate eigenvalues and eigenvectors from the principal components analysis over two time periods: 1994–2000 and 2001–2008. The results in Table 2 show that the first principal component captures 77% of variability among financial institutions in 1994–2000, which increases to 83% in 2001–2008. Together, the first and second components explain 92% of the return variation on average. The time-series graph of eigenvalues for all four principal components presented in Figure 1 shows that indeed the first and second principal components capture the majority of return variation during the whole sample. However, the first principal component is very dynamic capturing from 65% to 93% of return variation. The PC1 eigenvalue was increasing from the beginning of the sample, peaking at 93% in August 1998 during the LTCM crisis, and subsequently decreased. The PC1 eigenvalue started to increase in 2003 and stayed high through 2005 (the period when the Federal Reserve intervened and raised interest rates), declining slightly in 2006–2007, and increasing again in 2008, peaking in March 2008. As a result, the first principal component explained more than 80% of return variation over the Financial Crisis of 2007–2009.

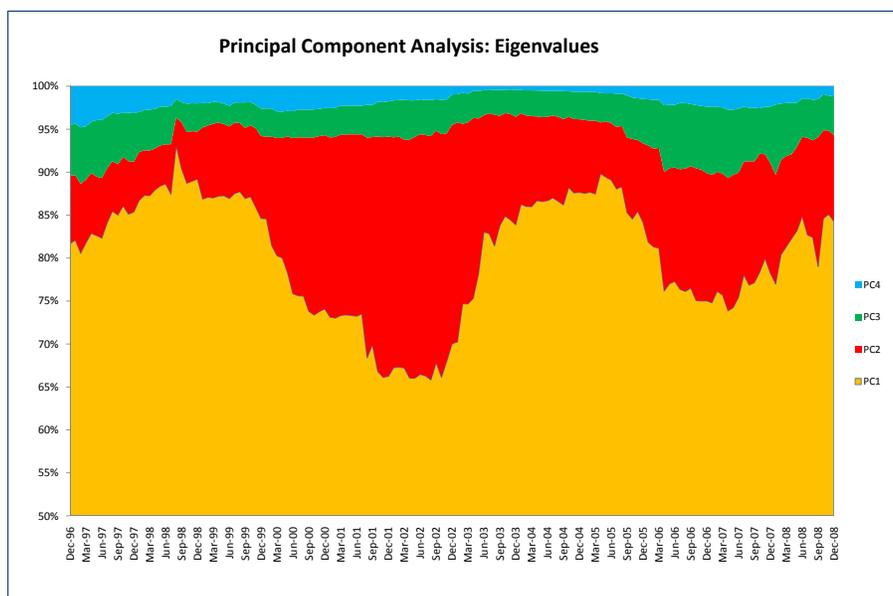


Figure 1: Principal components analysis of the monthly return indexes for Banks, Brokers, Insurers, and Hedge Funds over January 1994 to December 2008. 36-month rolling-window eigenvalues for principal components 1–4 are presented.

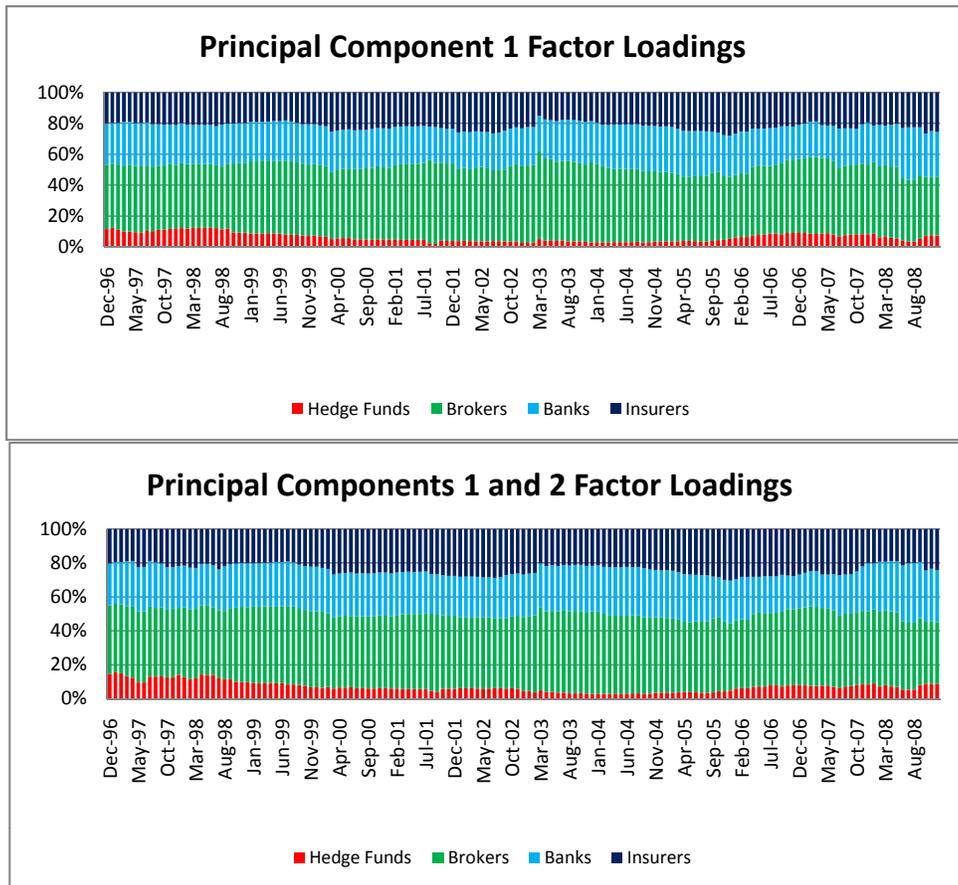


Figure 2: Principal components analysis of the monthly return indexes for Banks, Brokers, Insurers, and Hedge Funds over January 1994 to December 2008. 36-month rolling-window eigenvector exposures for principal component 1 and the sum of principal components 1 and 2 are presented.

Eigenvalues				
Sample Period	PC1	PC2	PC3	PC4
Hedge Funds, Brokers, Banks, Insurers				
1994 to 2000	77%	16%	4%	3%
2001 to 2008	83%	10%	6%	1%
Hedge-Fund Sectors				
1994 to 2000	61%	24%	9%	5%
2001 to 2008	69%	19%	10%	3%
Eigenvectors				
Index	PC1	PC2	PC3	PC4
1994 to 2000				
Hedge Funds	0.13	-0.18	0.84	0.50
Brokers	0.79	-0.57	-0.23	-0.02
Banks	0.45	0.49	0.41	-0.63
Insurers	0.40	0.64	-0.28	0.60
2001 to 2008				
Hedge Funds	0.10	-0.08	-0.22	0.97
Brokers	0.76	-0.64	0.02	-0.13
Banks	0.50	0.58	0.63	0.14
Insurers	0.41	0.50	-0.75	-0.17

Table 2: Principal components analysis of the monthly return indexes for financial institutions (Banks, Brokers, Insurers, and Hedge Funds) over two time periods: January 1994 to December 2000, and January 2001 to December 2008.

Table 2 contains factor loadings for 1994–2000 and 2001–2008 and Figure 2 depicts 36-month rolling-window eigenvector exposures for PC1 and the sum of PC1 and PC2 for the whole sample, 1994–2008. The loadings on the first two principal components are quite persistent over time for all indexes. All loadings are significant at 5%, but we do find variation in the sensitivities of the indexes to the four principal components. For example, at 0.77, the sensitivity of the Broker returns to the first component is the largest on average, compared to only 0.12 for Hedge Funds. The sensitivity of Banks and Insurers to the first principal component is 0.47 and 0.40 on average, respectively.⁴ Hedge Funds seem to be quite independent of other financial institutions, with significant factor loadings on the third component (0.84 in 1994–2000) and on the fourth component (0.97 in 2001–2008). The exposures of Brokers, Banks, and Insurers to the third and fourth principal components are small. The third and fourth principal components explain only 4% and 3% of the total variation, respectively. Figure 2 also shows that during the whole sample the exposures of Hedge Funds to the first and second principal components were minimal, averaging only 7% of the total exposure. As a result, Hedge Funds do not contribute greatly to the covariance matrix of the four index returns. In summary, the first and second principal components affect mostly Brokers, Banks, and Insurers, not Hedge Funds.⁵

The eigenvector of the second principal component (PC2) captures two distinct groups of financial institutions: Group 1 (Hedge Funds and Brokers that have negative factor loadings on PC2) and Group 2 (Banks and Insurers that have positive factor loadings on PC2). The groupings are plausible given the various business relationships and similarities among these institutions.

5.2 Granger Causality Tests

In Table 3 we present p -values for linear Granger causality tests between months t and $t+1$ among the monthly return indexes of Banks, Brokers, Insurers, Hedge Funds, and the S&P 500 for two samples: 1994–2000 and 2001–2008. The causality relationships for these two

⁴These averages are calculated by averaging principal components for the 1994–2000 and 2001–2008 periods.

⁵We also re-run the PCA analysis by scaling eigenvectors by each financial institution’s volatility. Given the relatively low volatility of Hedge Funds (Table 1), once this adjustment is made, the exposures of Hedge Funds to the first and second principal components were in line with those of other financial institutions. Specifically, each financial institution contributed about 0.25 to the total exposure. The loadings are also persistent over time. The results are available from the authors upon request.

samples are depicted in Figure 3. Relationships that are significant at 5% level are captured with arrows. Black arrows represent uni-directional causal relationships, and red arrows represent bi-directional causal relationships. All linear Granger-causality tests are adjusted for autocorrelation and heteroskedasticity.

	Hedge Funds	Brokers	Banks	Insurers	S&P 500	Hedge Funds	Brokers	Banks	Insurers	S&P 500
	Raw Returns									
	1994 to 2000					2001 to 2008				
Hedge Funds		84.0	31.4	69.4	51.1		24.1	50.5	19.8	65.2
Brokers	50.2		40.0	89.5	19.5	0.0		8.0	0.9	19.9
Banks	48.6	87.2		88.3	31.7	0.0	25.3		8.5	35.1
Insurers	26.5	44.9	5.2		85.0	0.0	0.1	3.1		4.0
S&P 500	66.1	89.0	55.2	69.1		0.0	1.9	6.2	1.2	
	Residual Returns									
	1994 to 2000					2001 to 2008				
Hedge Funds		24.5	43.2	53.6	NA		99.2	76.3	80.1	NA
Brokers	28.7		33.9	48.2	NA	36.4		97.5	21.6	NA
Banks	17.5	39.7		24.0	NA	4.7	54.2		97.0	NA
Insurers	27.8	91.1	87.1		NA	40.1	6.3	73.8		NA
S&P 500	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Table 3: p -values of linear Granger-causality test statistics for the monthly returns and monthly residual returns (from regressions on the monthly returns of the S&P 500) of Hedge Funds, Brokers, Banks, and Insurers over two samples: January 1994 to December 2000, and January 2001 to December 2008. Statistics that are significant at 5% level are shown in bold, and p -values are adjusted for autocorrelation and heteroskedasticity.

We do not observe any significant causal relationships between Banks, Brokers, Insurers, and Hedge Funds in the first part of the sample (1994–2000). However, in the second half of the sample (2001–2008) we find that all financial institutions became highly linked. Hedge Funds were causally affected by Banks, Brokers, and Insurers, though, they did not affect any other financial institutions. Moreover, bi-directional relationships between Brokers and Insurers emerged. Banks were only affected by Insurers. Therefore, in stark contrast to 1994–2000, all four sectors of the finance and insurance industry became connected in 2001–2008. In 1994–2000 we find that none of the financial institutions had any forecast power for future changes in S&P 500 returns, but in 2001–2008, Insurers Granger-caused S&P 500 returns.

These results are surprising because these financial institutions invest in different assets

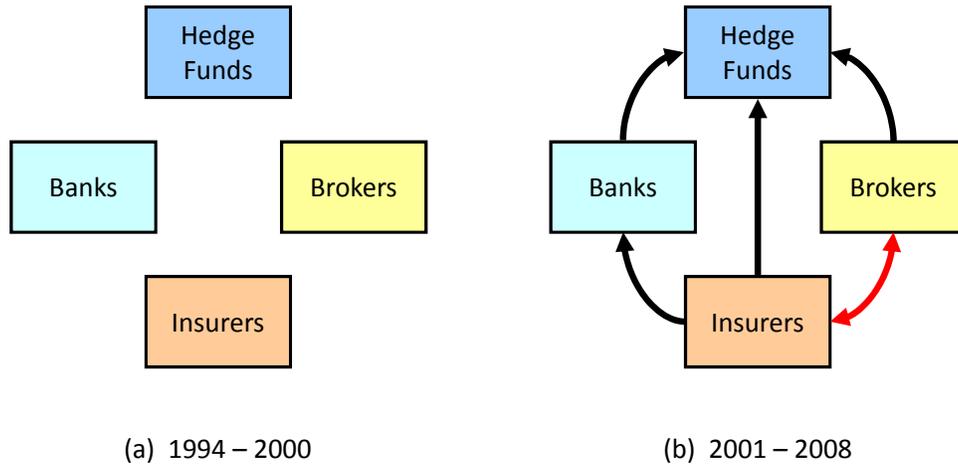


Figure 3: Linear Granger-causality relationships (at the 5% level of statistical significance) among the monthly returns of Banks, Brokers, Insurers, and Hedge Funds over two samples: (a) January 1994 to December 2000, and (b) January 2001 to December 2008. All p -values are adjusted for autocorrelation and heteroskedasticity.

and operate in different markets. However, all these financial institutions rely on leverage, which may be innocuous from each institution’s perspective, but from a broader perspective, diversification may be reduced and systemic risk increased. The linear Granger-causality tests show that a liquidity shock to one sector propagates to other sectors, eventually culminating in losses, defaults, and a systemic event. This possibility will become clearer when we turn to the Granger-causality network map of individual financial institutions in Section 5.3.

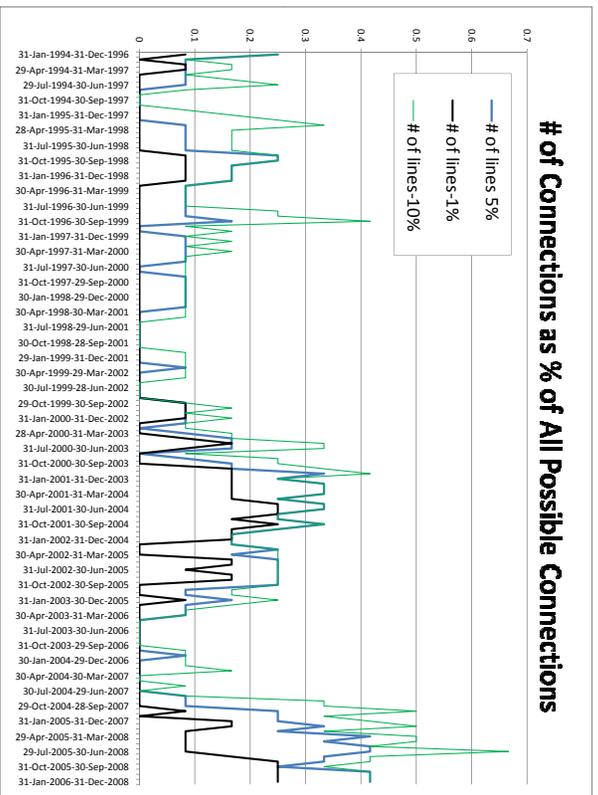
We also investigate dynamic causality among the return indexes of Banks, Brokers, Insurers, and Hedge Funds using a 36-month rolling window. The results are presented in Figure 4. Specifically, we calculate the proportion of significant causal relationships at 1%, 5%, and 10% significance levels out of the total possible causal relationships (12 for 4 indexes) and graph this fraction over time. We find Granger causality is generally present in the second part of the sample (after 2001). This is in line with our original methodology of splitting the total time periods into two samples: 1994–2000 and 2001–2008. The presence of significant causal relationships can be attributed to the existence of frictions in the financial and insurance system. As discussed above, Value-at-Risk constraints and other market frictions such as transaction costs, borrowing constraints, costs of gathering and process-

ing information, and institutional restrictions on shortsales may lead to Granger causality among price changes of financial assets. Specifically, after the LTCM crisis and the Internet Crash of 2000, the financial system started to exhibit these frictions. Figure 4 also depicts the presence of Granger causality to Hedge Funds over time at the 5% level of significance. Consistent with results found in Table 3 and depicted in Figure 3, Hedge Funds are largely causally affected by other financial institutions starting in 2001. The exception is the period associated with the failure of the Amaranth hedge fund in 2006.

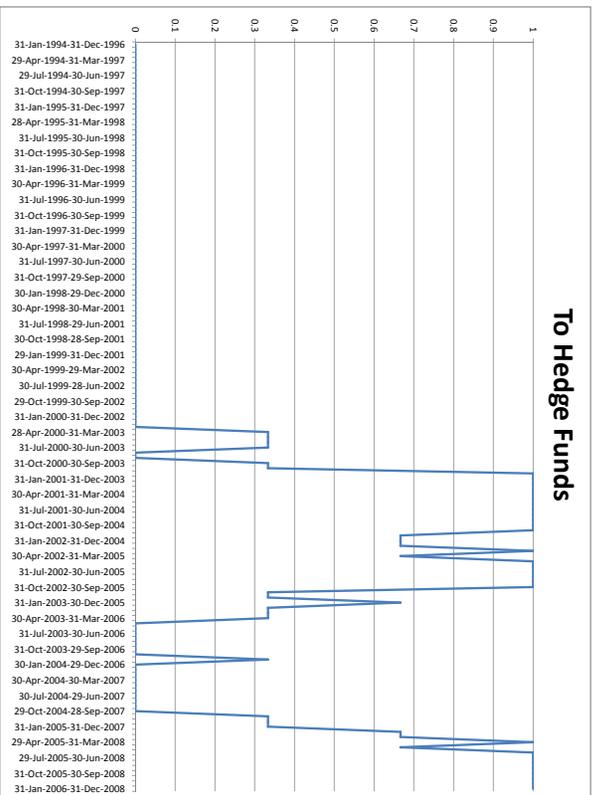
These results are also surprising since we are using heteroskedasticity- and autocorrelation-adjusted test statistics for the monthly returns of aggregate indexes. In a framework where all markets clear and past information is reflected in current prices, returns should not exhibit any systemic time-series patterns. However, our results are consistent with Danielsson et al. (2009) who show that risk-neutral traders operating under Value-at-Risk constraints can amplify market shocks through feedback effects. Our results are also consistent with Battiston et al. (2009) who generate the endogenous emergence of systemic risk in a credit network among financial institutions. Individual financial fragility feeds back on itself, amplifying the initial shock and leading to systemic crisis.

Our systemic risk measure is based on causal interconnectedness between financial institutions, which captures both contagion effects between financial institutions as well as exposures among all financial institutions to a common factor, e.g., the U.S. equity market. To separate contagion effects and common-factor exposure, we re-estimate Granger-causality relationships using the residuals of the four index returns from regressions against the S&P 500. While this procedure should eliminate the single largest common factor from the four indexes, it may also eliminate some of the genuine connections among financial institutions because the financial sector represents about 23% of the S&P 500 capitalization (until 2006) and because the “financial market” is not a passive actor, but contributes to endogenous feedbacks among financial institutions. Therefore, the results for the residuals may be viewed as a conservative upper bound on the impact of the common factor in determining Granger-causal relationships among the four indexes.

Table 3 presents the p -values of linear Granger causality test statistics for the monthly residual returns of Hedge Funds, Brokers, Banks, and Insurers over the same two samples: 1994–2000 and 2001–2008. The results for these two sub-samples are depicted in Figure 5. For the 1994–2000 sample, the results in Figure 5 are similar to those in Figure 3 where we



(a)



(b)

Figure 4: The proportion of significant causal relationships out of a possible total of 12 relationships based on 36-month rolling-window linear Granger-causality relationships over the period from January 1994 to December 2008: (a) among the monthly returns of Banks, Brokers, Insurers, and Hedge Funds at the 1%, 5%, and 10% levels of statistical significance; and (b) for the monthly returns of Banks, Brokers, and Insurers to Hedge Funds at the 5% level. All p -values are adjusted for autocorrelation and heteroskedasticity.

	1994 to 2008				2001 to 2008			
	Hedge Funds	Brokers	Banks	Insurers	Hedge Funds	Brokers	Banks	Insurers
Hedge Funds		0.0	0.0	0.0		0.3	1.3	8.8
Brokers	0.0		23.7	74.9	0.0		0.0	94.2
Banks	1.7	0.0		78.1	21.4	0.7		0.0
Insurers	6.7	82.0	93.1		36.6	0.2	0.0	

Table 4: p -values of nonlinear Granger-causality likelihood ratio tests for the monthly residual returns indexes of Banks, Brokers, Insurers, and Hedge Funds for two sub-samples: January 1994 to December 2000, and January 2001 to December 2008. Statistics that are significant at 5% level are shown in bold. All p -values are adjusted for autocorrelation and heteroskedasticity.

the volatilities of financial institutions. With nonlinear Granger-causality tests we find more interconnectedness between financial institutions compared to linear Granger-causality results, which supports the endogenous volatility feedback relationship proposed by Danielsson, Shin, and Zigrand (2009). The nonlinear Granger-causality results are also consistent with the results of the linear Granger-causality tests in two respects: the connections are increasing over time, and even after controlling for the S&P 500, shocks to one financial institution are likely to spread to all other financial institutions.

5.3 Network Diagrams

To fully appreciate the impact of Granger-causal relationships among various financial institutions, we provide a visualization of the results of linear Granger-causality tests applied over 36-month rolling sub-periods to the 25 largest institutions (as determined by average AUM for hedge funds and average market capitalization for brokers, insurers, and banks during the time period considered) in each of the four index categories.⁸

The composition of this sample of 100 financial institutions changes over time as assets under management change, and as financial institutions are added or deleted from the sample. Granger-causality relationships are drawn as straight lines connecting two institutions, with the color representing the type of institution that is “causing” the relationship, i.e., the

⁸Given that hedge-fund returns are only available monthly, we impose a minimum of 36 months to obtain reliable estimates of Granger-causal relationships. We also used a rolling window of 60 months to control the robustness of the results. Results are provided upon request.

institution at date- t which Granger-causes the returns of another institution at date $t+1$. Green indicates a broker, red indicates a hedge fund, black indicates an insurer, and blue indicates a bank. Only those relationships significant at 5% level are depicted. The time-series of the number of connections as a % of all possible connections is depicted in Figure 6. According to Figure 6, the number of connections are large and significant during the LTCM 1998 crisis, 2002–2004 (period of low interest rates and high leverage in financial institutions), and the recent Financial Crisis of 2007–2009.⁹ To conserve space, we tabulate results only for five of the 36-month rolling-window 145 sub-periods in Figures 7–11: 1994–1996, 1996–1998, 1999–2001, 2002–2004, and 2006–2008. These are representative time-periods encompassing both tranquil, boom, and bust periods in the sample as shown in Figure 6.¹⁰

For each sub-period, we also provide summary statistics for the monthly returns of 100 largest (with respect to AUM) financial institutions in Table 5, including the asset-weighted autocorrelation, the normalized number of connections,¹¹ and the total number of connections.

We find that Granger-causality relationships are highly dynamic among these financial institutions. Results are presented in Table 5 and Figures 7–11. For example, the total number of connections between financial institutions was 583 in the beginning of the sample (1994–1996), but it more than doubled to 1,244 at the end of the sample (2006–2008). We also find that during and before financial crises the financial system becomes much more interconnected in comparison to more tranquil periods. For example, the financial system was highly interconnected during the LTCM 1998 crisis and the most recent Financial Crisis of 2007–2009. In the relatively tranquil period of 1994–1996, the total number of connections as a percentage of all possible connections was 6% and the total number of connections among financial institutions was 583. Right before and during the LTCM 1998 crisis (1996–1998), the number of connections increased by 50% to 856 encompassing 9% of all possible connections. In 2002–2004, the total number of connections was just 611 (6% of total possible connections), and that more than doubled to 1244 connections (13% of total possible

⁹More detailed analysis of the significance of Granger-causal relationships is provided in the robustness analysis of Section 6.1.

¹⁰To fully appreciate the dynamic nature of these connections, we have created a short animation using 36-month rolling-window network diagrams updated every month from January 1994 to December 2008, which can be viewed at <http://web.mit.edu/alo/www>.

¹¹The normalized number of connections is the fraction of all statistically significant connections (at the 5% level) between the n financial institutions out of all $n(n-1)$ possible connections.

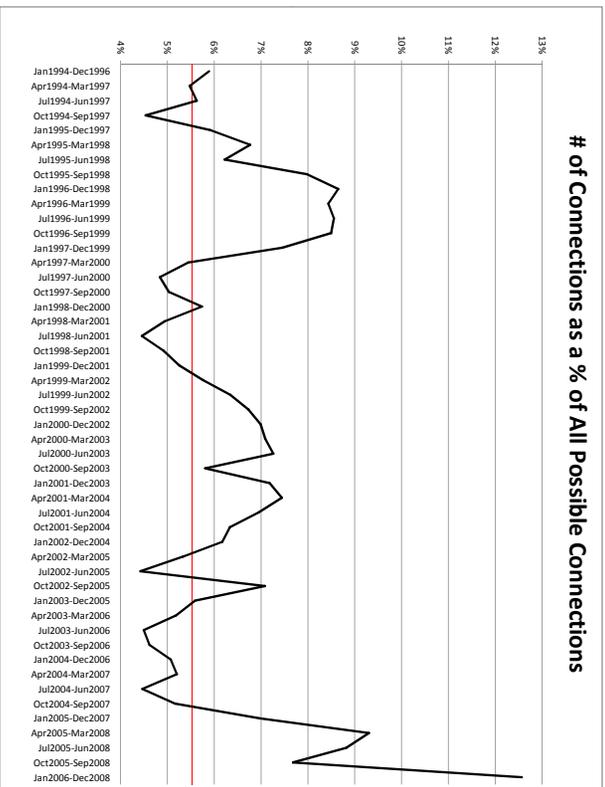


Figure 6: The time series of linear Granger-causality relationships (at the 5% level of statistical significance) among the monthly returns of the largest 25 banks, brokers, insurers, and hedge funds (as determined by average AUM for hedge funds and average market capitalization for brokers, insurers, and banks during the time period considered) for 36-month rolling-window sample periods from January 1994 to December 2008. The # of connections as a % of all possible connections is depicted in black against 0.055, the 95% of the simulated distribution obtained under the hypothesis of no causal relationships depicted in red. All p -values are adjusted for autocorrelation and heteroskedasticity.

Sector	Asset Weighted AutoCorr	# of Connections as % of All Possible Connections				# of Connections			
		Hedge Funds	Brokers	Banks	Insurers	Hedge Funds	Brokers	Banks	Insurers
January 1994 to December 1996									
All	-0.07	6%				583			
Hedge Funds	0.03	7%	3%	6%	6%	41	21	36	37
Brokers	-0.15	3%	5%	6%	4%	18	29	36	24
Banks	-0.03	6%	7%	9%	7%	40	46	54	44
Insurers	-0.10	5%	6%	6%	9%	33	38	35	51
January 1996 to December 1998									
All	-0.03	9%				856			
Hedge Funds	0.08	14%	6%	5%	3%	82	38	30	20
Brokers	-0.04	13%	9%	9%	9%	81	53	54	57
Banks	-0.09	11%	8%	11%	10%	71	52	65	64
Insurers	0.02	9%	9%	7%	6%	57	54	44	34
January 1999 to December 2001									
All	-0.09	5%				520			
Hedge Funds	0.17	5%	5%	5%	9%	32	32	33	58
Brokers	0.03	8%	9%	3%	5%	53	52	19	29
Banks	-0.09	5%	3%	4%	7%	30	17	25	42
Insurers	-0.20	5%	3%	2%	6%	32	16	14	36
January 2002 to December 2004									
All	-0.08	6%				611			
Hedge Funds	0.20	10%	3%	9%	5%	61	20	56	29
Brokers	-0.09	8%	4%	4%	6%	53	23	26	39
Banks	-0.14	9%	3%	4%	5%	55	16	24	30
Insurers	0.00	8%	6%	9%	6%	48	40	55	36
January 2006 to December 2008									
All	0.08	13%				1244			
Hedge Funds	0.23	10%	13%	5%	13%	57	82	31	83
Brokers	0.23	12%	17%	9%	12%	78	102	55	73
Banks	0.02	23%	12%	10%	9%	142	74	58	54
Insurers	0.12	13%	16%	12%	16%	84	102	73	96

Table 5: Summary statistics of linear Granger-causality relationships (at the 5% level of statistical significance) among the monthly returns of the largest 25 banks, brokers, insurers, and hedge funds (as determined by average AUM for hedge funds and average market capitalization for brokers, insurers, and banks during the time period considered) for five sample periods: January 1994 to December 1996, January 1996 to December 1998, January 1999 to December 2001, January 2002 to December 2004, and January 2006 to December 2008. Asset-weighted autocorrelations, the normalized number of connections, and the total number of connections for all financial institutions, hedge funds, brokers, banks, and insurers are calculated for each sample, and all p -values are adjusted for autocorrelation and heteroskedasticity.

Jan1994-Dec1996

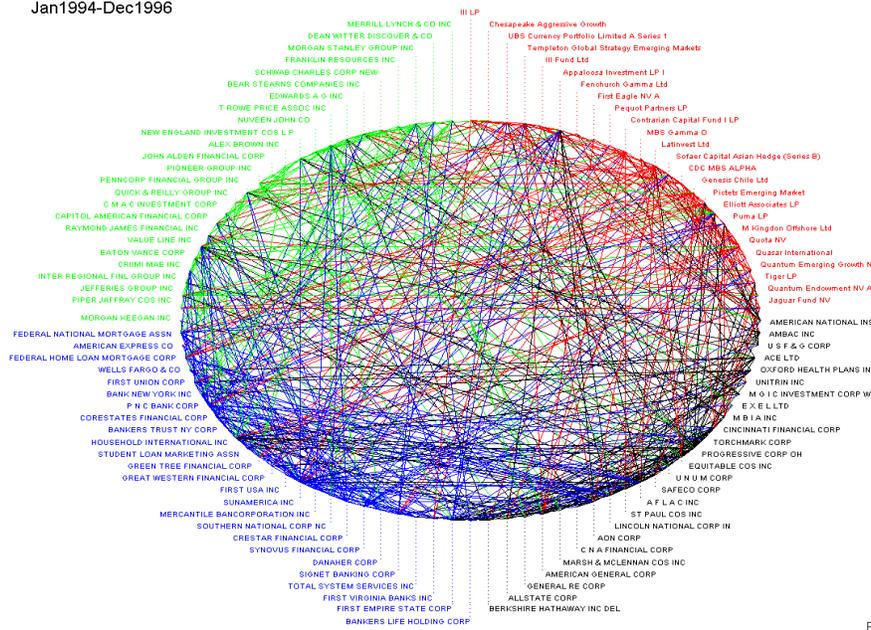


Figure 7: Network Diagram of Linear Granger-causality relationships that are statistically significant at 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 1994 to December 1996. The type of institution causing the relationship is indicated by color: green for brokers, red for hedge funds, black for insurers, and blue for banks. All p -values are adjusted for autocorrelation and heteroskedasticity.

connections) in 2006–2008, which was right before and during the recent Financial Crisis of 2007–2009 according to Table 5. Both the LTCM 1998 crisis and the Financial Crisis of 2007–2009 were associated with liquidity and credit problems. The increase in interconnections between financial institutions is a significant systemic risk indicator, especially for the Financial Crisis of 2007–2009 which experienced the largest number of interconnections compared to other time-periods.¹²

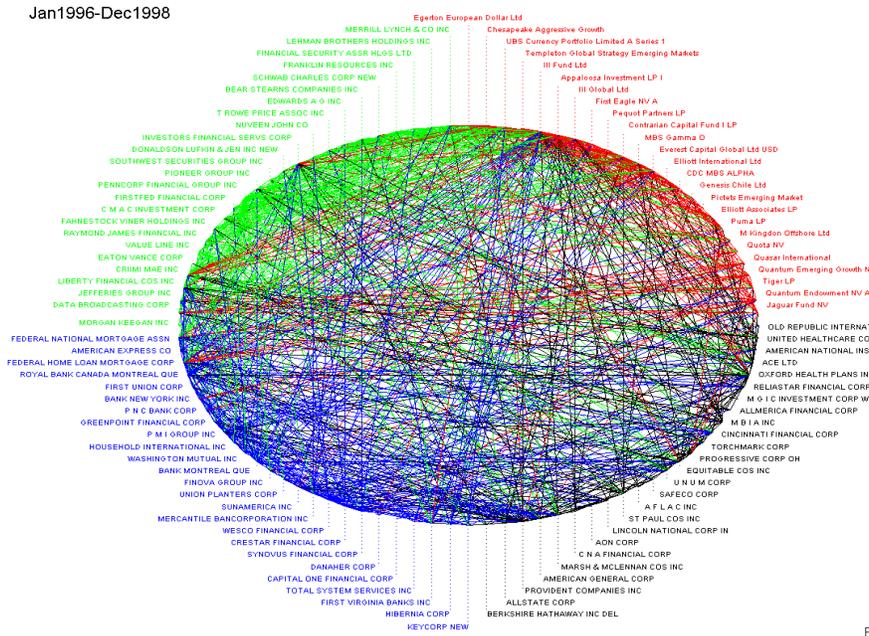


Figure 8: Network diagram of linear Granger-causality relationships that are statistically significant at 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 1996 to December 1998. The type of institution causing the relationship is indicated by color: green for brokers, red for hedge funds, black for insurers, and blue for banks. All p -values are adjusted for autocorrelation and heteroskedasticity.

By measuring Granger-causal connections among individual financial institutions, we see that during the LTCM 1998 crisis (1996–1998 period), hedge funds were greatly interconnected with other hedge funds, banks, brokers, and insurers. Their impact on other financial institutions was substantial, though less than the total impact of other financial institutions on them. In the aftermath of the crisis (1999–2001 and 2002–2004 time periods), the number of financial connections decreased, especially links affecting hedge funds. The total number of connections clearly started to increase just before and in the beginning of the recent

¹²The results are similar when we adjust for the S&P 500, and are available upon request.

Financial Crisis of 2007–2009 (2006–2008 time period). In that time period, hedge funds had significant bi-lateral relationships with insurers and brokers. Hedge funds were highly affected by banks (23% of total possible connections), though they did not reciprocate in affecting the banks (5% of total possible connections). The number of significant Granger-causal relations from banks to hedge funds, 142, was the highest between these two sectors across all five sample periods. In comparison, hedge funds Granger-caused only 31 banks. These results for the largest individual financial institutions are consistent with our index results, suggesting that banks may be of more concern than the “shadow banking system” from the perspective of systemic risk.

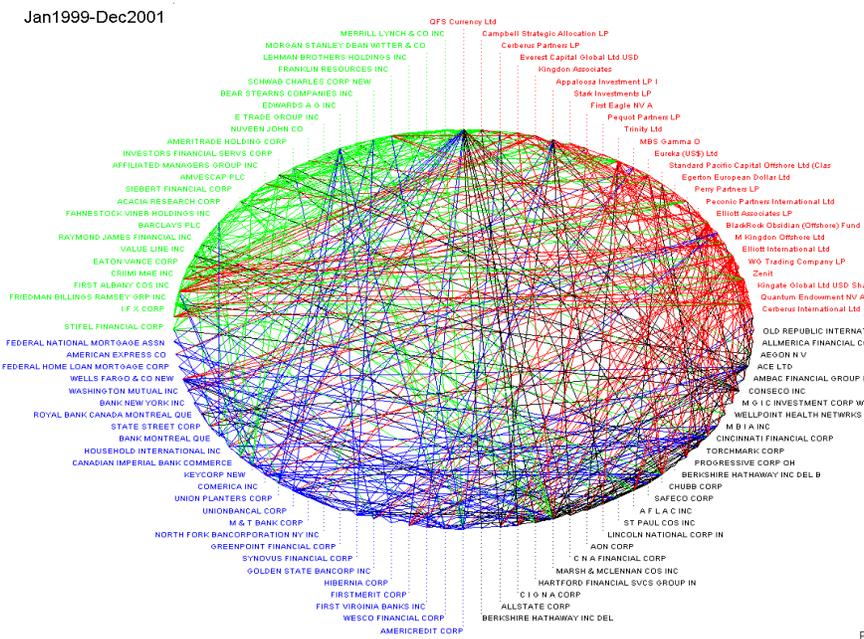


Figure 9: Network diagram of linear Granger-causality relationships that are statistically significant at 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 1999 to December 2001. The type of institution causing the relationship is indicated by color: green for brokers, red for hedge funds, black for insurers, and blue for banks. All p -values are adjusted for autocorrelation and heteroskedasticity.

Lo (2002) and Getmansky, Lo, and Makarov (2004) suggest using return autocorrelations to gauge the illiquidity risk exposure, hence we report asset-weighted autocorrelations in Table 5. We find that the asset-weighted autocorrelations for all financial institutions were negative for the first four time periods, however, in 2006–2008, the period that includes the recent financial crisis, the autocorrelation becomes positive. When we separate

the asset-weighted autocorrelations by sector, we find that during all periods, hedge-fund asset-weighted autocorrelations were positive, but were mostly negative for all other financial institutions.¹³ However, in the last sample period (2006–2008), the asset-weighted autocorrelations became positive for all financial institutions. These results suggest that the period of the Financial Crisis of 2007–2009 exhibited the most illiquidity and connectivity among financial institutions.

In summary, we find that, on average, all companies in the four sectors we studied have become highly interrelated and generally less liquid over the past decade, increasing the level of systemic risk in the finance and insurance industries.

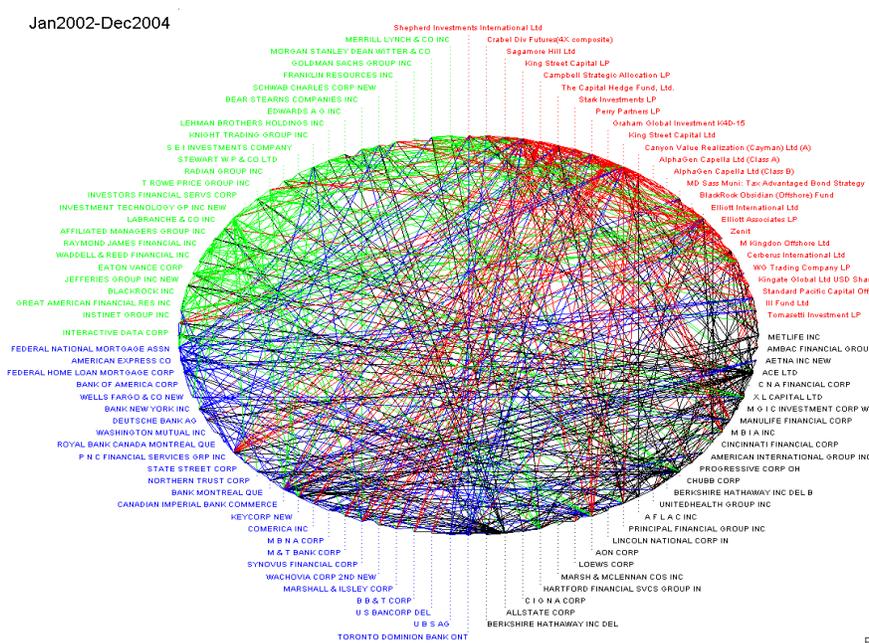


Figure 10: Network diagram of linear Granger-causality relationships that are statistically significant at 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 2002 to December 2004. The type of institution causing the relationship is indicated by color: green for brokers, red for hedge funds, black for insurers, and blue for banks. All p -values are adjusted for autocorrelation and heteroskedasticity.

To separate contagion and common-factor exposure, we regress each company’s monthly returns on the S&P 500 and re-run the linear Granger causality tests on the residuals. We

¹³Starting in the October 2002–September 2005 period, the overall system and individual financial-institution 36-month rolling-window autocorrelations became positive and remained positive through the end of the sample.

Jan2006-Dec2008

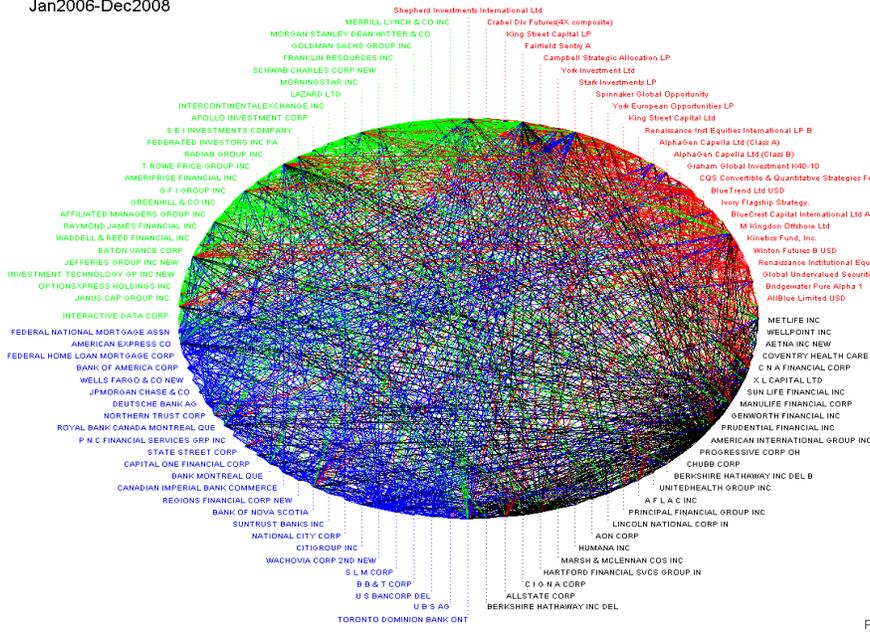


Figure 11: Network diagram of linear Granger-causality relationships that are statistically significant at 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 2006 to December 2008. The type of institution causing the relationship is indicated by color: green for brokers, red for hedge funds, black for insurers, and blue for banks. All p -values are adjusted for autocorrelation and heteroskedasticity.

find the same pattern of dynamic interconnectedness between financial institutions, and the resulting network diagrams are qualitatively similar to those with raw returns, hence we omit them to conserve space.¹⁴

5.4 Early Warning Signals of the Financial Crisis of 2007–2009

One natural application of any systemic risk measure is to provide an actionable early warning signal. In this section, we construct an array of such indicators based on the Granger-causality networks of Section 5.3 and principal components analysis of Section 5.1, and apply it to specific financial institutions. Following the approach of Acharya et al. (2010), we consider two 36-month samples, October 2002–September 2005 and July 2004–June 2007, as estimation periods in which systemic risk measures are estimated, and the period from July 2007–December 2008 as the “out-of-sample” period encompassing the Financial Crisis of 2007–2009. The October 2002–September 2005 period is chosen because this is the last 36-month rolling sub-period before the Financial Crisis of 2007–2009 in which the number of connections was statistically different from zero, and the overall system and individual financial-institution autocorrelations became and stayed positive before the Financial Crisis of 2007–2009. July 2004–June 2007 is considered because this is the last 36-month sub-period before the recent crisis. For each financial institution, we compute the following set of systemic risk measures (the first eight are based on Granger-causality network diagrams and the last one is based on principal components analysis):

- **Number of “In” Connections:** The number of financial institutions that significantly Granger-cause this financial institution.
- **Number of “Out” Connections:** The number of financial institutions that are significantly Granger-caused by this financial institution.
- **Number of “In+Out” Connections:** The sum of “In” and “Out” connections.
- **Number of “In-from-Other” Connections:** The number of other types of financial institutions that significantly Granger-cause this financial institution. For example, for a hedge fund, “other types” are banks, brokers, and insurers.

¹⁴Network diagrams for residual returns (from a market-model regression against the S&P 500) are available upon request.

- **Number of “Out-to-Other” Connections:** The number of other types of financial institutions that are significantly Granger-caused by this financial institution.
- **Number of “In+Out Other” Connections:** The sum of “In-from-Other” and “Out-to-Other” connections.
- **Closeness:** The shortest path between a financial institution and all other financial institutions reachable from it, averaged across all other financial institutions.
- **Eigenvector Centrality:** A measure of the importance of a financial institution in a network, which assigns relative scores to financial institutions in the network based on the principle that connections to high-scoring financial institutions contribute more to the score of the financial institution in question than equal connections to low-scoring financial institutions.¹⁵
- **PCA:** The total absolute exposure of a financial institution to the first 20 principal components weighted by the percentage of the variance explained by each principal component.

As in Section 5.3, for each of the four categories we consider the top 25 financial institutions as determined by the average AUM for hedge funds and average market capitalization for brokers, insurers, and banks during the time period considered, yielding 100 entities in all. For each systemic risk measure, financial institutions are ranked from 1 to 100.

To evaluate the predictive power of these rankings, we first compute the maximum percentage financial loss (Max%Loss) suffered by each of the 100 institutions during the crisis period from July 2007 to December 2008.¹⁶ We then rank all financial institutions from 1 to 100 according to Max%Loss. We then estimate univariate regressions for Max%Loss rankings on the institutions’ systemic-risk rankings. The results are reported in Table 6 for two samples: October 2002–September 2005 and July 2004–June 2007. For each regression,

¹⁵Specifically, for a network with n nodes, let \mathbf{A} be the “adjacency matrix”, the $(n \times n)$ -matrix of 0’s and 1’s in which the (i, j) -th element is 1 if there is a connection between nodes i and j , and 0 otherwise. The eigenvector centrality measure is the eigenvector corresponding to the largest eigenvalue of \mathbf{A} . See Newman (2010) for details.

¹⁶The maximum percentage loss for a financial institution is defined to be the difference between the market capitalization of the institution (fund size in the case of hedge funds) at the end of June 2007 and the minimum market capitalization during the period from July 2007 to December 2008 divided by the market capitalization or fund size of the institution at the end of June 2007.

we report the β coefficient, the t -statistic, p -value, and the Kendall (1938) τ rank-correlation coefficient.

Statistic	Max % Loss (2005)				Max % Loss (2007)			
	Coeff	t-stat	p-value	Kendall τ	Coeff	t-stat	p-value	Kendall τ
# of "In" Connections	0.03	0.25	0.80	0.02	-0.01	-0.07	0.94	-0.01
# of "Out" Connections	0.23	2.23	0.03	0.16	0.25	2.53	0.01	0.20
# of "In+Out" Connections	0.16	1.51	0.13	0.11	0.19	1.89	0.06	0.13
# of "In-from-Other" Connections	0.12	1.15	0.25	0.09	-0.02	-0.19	0.85	-0.02
# of "Out-to-Other" Connections	0.32	3.11	0.00	0.22	0.17	1.68	0.10	0.13
# of "In+Out Other" Connections	0.23	2.23	0.03	0.15	0.09	0.84	0.41	0.06
Closeness	0.23	2.23	0.03	0.16	0.25	2.53	0.01	0.20
Eigenvector Centrality	0.24	2.31	0.02	0.16	0.24	2.44	0.02	0.17
PCA	0.32	3.11	0.00	0.24	0.16	1.51	0.13	0.12

Table 6: Regression coefficients, t -statistics, p -values, and Kendall τ rank-correlation coefficients for regressions of maximum percentage loss on systemic risk measures. The maximum percentage loss for a financial institution is the dollar amount of the maximum cumulative decline in market capitalization or fund size for each financial institution during July 2007–December 2008 divided by the market capitalization or total fund size of the institution at the end of June 2007. Systemic risk measures are calculated over two samples: October 2002–September 2005 and July 2004–June 2007. Statistics that are significant at 5% level are displayed in bold.

We find that Out, Out-to-Other, In+Out Other, Closeness, Eigenvector Centrality, and PCA are significant determinants of the Max%Loss variable.¹⁷ Based on the Closeness and Eigenvector Centrality measures, financial institutions that are systemically important and are very interconnected are the ones that suffered the most during the Financial Crisis of 2007–2009. However, the institutions that declined the most during the Crisis were the ones that greatly affected other institutions—both their own and other types—and not the institutions that were affected by others. Both Out and Out-to-Other are significant, whereas In and In-from-Other are not. The top names in the Out and Out-to-Other categories include Wells Fargo, Bank of America, Citigroup, Federal National Mortgage Association, UBS, Lehman Brothers Holdings, Wachovia, Bank New York, American International Group, and Washington Mutual.¹⁸ In addition to causal relationships, contemporaneous correlations

¹⁷We have also analyzed the maximum financial loss in dollar terms (MaxLoss) for each of the 100 institutions from July 2007 to December 2008, which is defined as the difference between the market capitalization of the institution (or fund size in the case of hedge funds) at the end of June 2007 and the minimum market capitalization during the period from July 2007 to December 2008. For MaxLoss, Out-to-Other and Eigenvector Centrality are significant at 5% level and Out, In+Out Other, Closeness, and PCA are significant at 10%.

¹⁸The top 20 ranked financial institutions with respect to the Out-to-Other systemic risk measure are listed in Table 8.

between financial institutions served as predictors of the crisis. Based on the significance of the PCA measure, companies that were more correlated and associated with other companies, were more likely to suffer significant losses during the recent crisis.¹⁹

Consistent with the empirical results of Sections 5.1–5.3, banks, brokers, and insurance companies are systemically more important than hedge funds. As early as 2002–2005, important connections among these financial institutions were established that later contributed to the Financial Crisis and the subsequent decline of many of them.²⁰

6 Robustness Analysis

In this section, we check the robustness of our main results. In Section 6.1, we test the significance of our Granger-causality results. In Sections 6.2 and 6.3, we consider leverage and liquidity effects, respectively. Finally, in Section 6.4, we consider whether our systemic risk measures can predict future losses among individual financial institutions.

6.1 Significance of Granger-Causal Relationships

In this section we check for the possibility that Granger-causal relationships observed in the sample are due to chance. We first re-examine our results in Section 5.2 by conducting those inferences at the 1% level, and the results are depicted in Figure 4. Even at the 1% level, when the 1998, 2003–2005, and 2007–2008 periods are considered, we find significant causal relationships between the indexes of Banks, Hedge Funds, Insurers, and Brokers. In particular, at the 1% significance level, in 2005–2008, the period before and during the recent financial crisis, we observe 25% significant connections among indexes of financial and insurance institutions.

To test whether Granger-causal relationships between individual financial and insurance institutions are due to chance, we conduct a Monte Carlo simulation analysis. Specifically, assuming independence among financial institutions, we randomly simulate 100 time series representing the 100 financial institutions' returns in our sample, and test for Granger causality at the 5% level among all possible causal relationships (as in the empirical analysis in

¹⁹The significance of the PCA measure decreased in July 2004–June 2007. This is consistent with the result in Figure 1 where, for the monthly return indexes, the first principal component captured less of return variation during this time period than in the October 2002–September 2005 period.

²⁰We also consider time periods after October 2002–September 2005, and the results are still significant for Out, Out-to-Other, In+Out Other, Closeness, Eigenvector Centrality, and PCA measures.

Section 5.3, there are a total of 9,900 possible causal relationships), and record the number of significant connections. We repeat this exercise 500 times, and the resulting distribution is given in Figure 12. This distribution is centered at 0.052, which represents the fraction of significant connections among all possible connections under the null hypothesis of no statistical relation among any of the financial institutions. The area between 0.049 and 0.055 captures 90% of the simulations. Therefore, if we observe more than 5.5% of significant relationships in the real data, our results are unlikely to be the result of type I error.

We also conduct a similar simulation under the null hypothesis of contemporaneously correlated returns due to the S&P 500, but no causal relations among financial institutions (see the Appendix for details). The results are essentially the same, as seen in the histogram in Figure 12: the histogram is centered around 0.052, and the area between 0.048 and 0.055 captures 90% of the simulations.

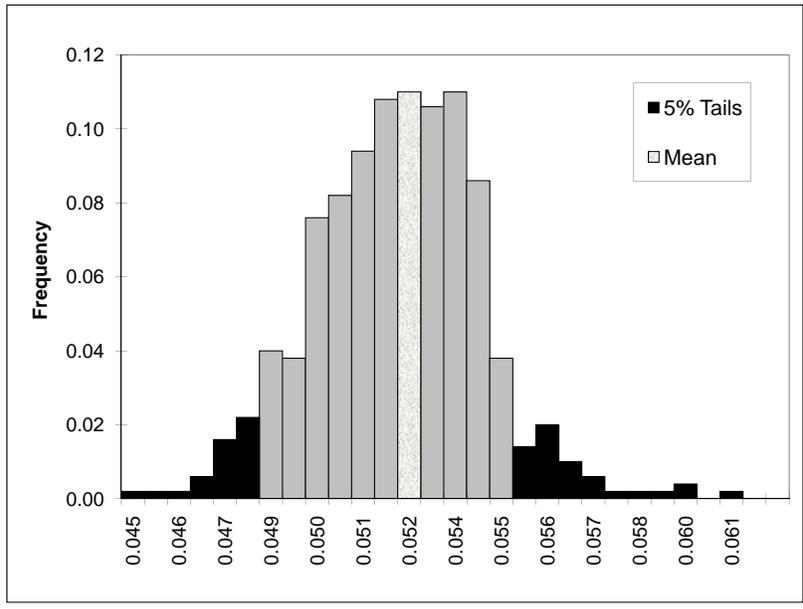
In Figure 6 we graph the total number of connections as a percentage of all possible connections we observe in the real data at the 5% significance level (in black) against 0.055, the 95th percentile of the simulated distribution obtained under the hypothesis of no causal relationships (in red). We see that when the 1998–1999, 2002–2004, and 2007–2008 periods are included in the analysis, the number of causal relationships observed far exceeds the number obtained purely by chance. Therefore, for these time-periods we can affirm that the observed causal relationships are statistically significant.²¹

6.2 Leverage Effects

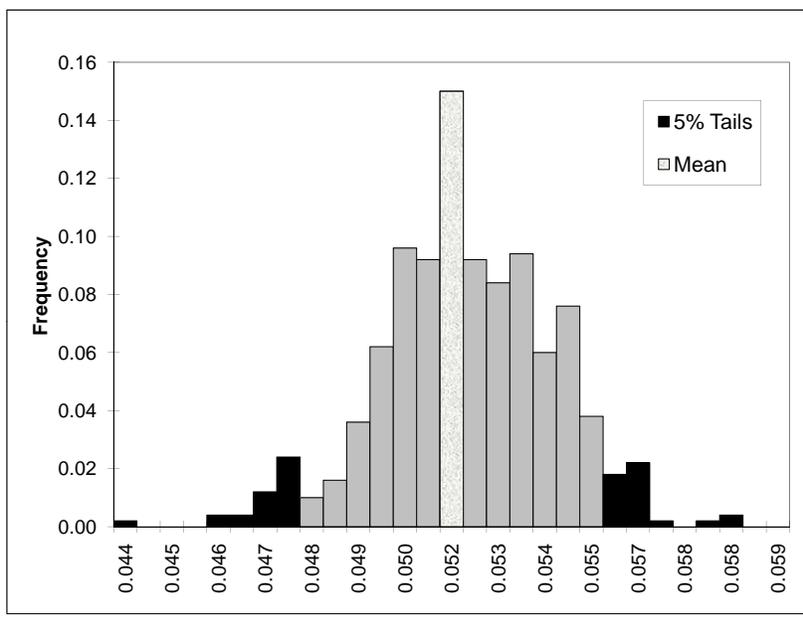
In this section, we consider whether some of our results can be explained by accounting for leverage effects.²² Leverage has the effect of a magnifying glass, expanding small profit opportunities into larger ones, but also expanding small losses into larger losses. And when unexpected adverse market conditions reduce the value of the corresponding collateral, such events often trigger forced liquidations of large positions over short periods of time. Such efforts to reduce leverage can lead to systemic events as we have witnessed during the recent crisis. Since leverage information is not directly available, for publicly traded banks, brokers, and insurers, we estimate their leverage as the ratio of Total Assets minus Equity Market Value to Equity Market Value. For hedge funds, we use reported average leverage for a given

²¹The results are similar for the 1%-level of significance.

²²We thank Lasse Pedersen and Mark Carey for suggesting this line of inquiry.



(a)



(b)

Figure 12: Histograms of simulated Granger-causal relationships between financial institutions. 100 time series representing 100 financial institutions’s returns are simulated and tested for Granger causality at the 5% level. The number of significant connections out of all possible connections is calculated for 500 simulations. In histogram (a), independence among financial institutions is assumed. In histogram (b), contemporaneous correlation among financial institutions, captured through the dependence on the S&P 500 is allowed. See the Appendix for a more detailed description of the simulation.

time period. Using these crude proxies, we find that estimated leverage is positively related to future losses (Max%Loss).²³

We also estimated a multivariate regression in which we regressed Max%Loss for each financial institution during July 2007–December 2008 on PCA, Leverage, and systemic risk measures based on Granger causality (for each Granger-causality measure, we estimated a separate regression). The results are presented in Table 7. We find that Leverage and PCA are significant in all these regressions.²⁴ After adjusting for PCA and Leverage, we find that Out, In+Out, Out-to-Other, In+Out Other, Closeness, and Eigenvector Centrality are significant determinants of Max%Loss.²⁵ This is consistent with our main results. More importantly, we find that all our systemic risk measures are important, and capture different aspects of systemic risk. For example, both systemic risk measures based on Granger causality and principal components analysis served as early warning signals for the Financial Crisis of 2007–2009.

6.3 Liquidity Effects

Leverage is problematic largely because of illiquidity—in the event of a margin call on a leveraged portfolio, forced liquidations may cause even larger losses and additional margin calls, ultimately leading to a series of insolvencies and defaults as financial institutions withdraw credit. Lo (2002) and Getmansky, Lo, and Makarov (2004) suggest using return autocorrelation to gauge the illiquidity risk exposure of a given financial institution, hence we re-estimate the multivariate regression of Table 7 with the first-order autocorrelation of monthly returns as an additional regressor. All the patterns and inferences from Table 7 remain the same, even after controlling for leverage and liquidity effects as captured through autocorrelation. As shown in Table 5, the return autocorrelation of most financial institutions increased over time, and this trend may explain why the effects of liquidity/autocorrelation on future losses became significant in the July 2004–June 2007 period, serving as another warning signal for

²³When leverage is calculated over the October 2002–September 2005 time period and regressed on Max%Loss over the July 2007–December 2008 period, we obtain a slope coefficient of 0.22, a p -value of 0.04, and a τ rank-correlation coefficient of 0.16. The results are similar when the July 2004–June 2007 period is considered.

²⁴The correlation between leverage and our systemic risk measures is small and often negative, and in most cases, not statistically significant. Results are available upon request.

²⁵We also adjusted for asset size (as determined by AUM for hedge funds and market capitalization for brokers, insurers, and banks) and the results are not altered by including this additional regressor. In all regressions, asset size is not significant for Max%Loss. This may be due to the fact that our analysis is concentrated on large financial institutions (the top 25 for each sector). Results are available upon request.

Variable	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
October 2002 to September 2005														
Intercept	16.33	2.08	7.59	1.00	8.83	1.13	16.19	2.17	6.86	0.94	10.40	1.38	7.59	1.00
Leverage	0.23	2.26	0.25	2.59	0.25	2.54	0.23	2.22	0.28	2.87	0.25	2.52	0.25	2.59
PCA	0.33	3.17	0.29	2.93	0.31	3.11	0.31	2.97	0.22	2.15	0.27	2.67	0.29	2.93
# of "In" Connections	0.06	0.57												
# of "Out" Connections			0.28	2.77										
# of "In+Out" Connections					0.23	2.26								
# of "In-from-Other" Connections							0.08	0.76						
# of "Out-to-Other" Connections									0.34	3.26				
# of "In+Out Other" Connections											0.23	2.21		
Closeness													0.28	2.77
Eigenvector Centrality														0.25
R-square	0.16		0.23		0.21		0.16		0.26		0.21		0.23	0.22
July 2004 to June 2007														
Intercept	28.84	3.00	15.56	1.75	15.55	1.63	30.13	3.15	18.38	1.98	22.01	2.21	15.56	1.75
Leverage	0.18	1.72	0.23	2.25	0.21	2.10	0.18	1.72	0.22	2.13	0.20	1.91	0.23	2.25
PCA	0.17	1.59	0.16	1.57	0.21	2.02	0.16	1.55	0.17	1.65	0.19	1.82	0.16	1.57
# of "In" Connections	0.03	0.30												
# of "Out" Connections			0.28	2.80										
# of "In+Out" Connections					0.25	2.40								
# of "In-from-Other" Connections							0.01	0.09						
# of "Out-to-Other" Connections									0.22	2.11				
# of "In+Out Other" Connections											0.14	1.30		
Closeness													0.28	2.80
Eigenvector Centrality														0.27
R-square	0.06		0.13		0.11		0.06		0.10		0.07		0.13	0.13

Table 7: Parameter estimates of a multivariate regression of Max%Loss for each financial institution during July 2007–December 2008 on PCA, Leverage, and systemic risk measures based on Granger causality. The maximum percentage loss (Max%Loss) for a financial institution is the dollar amount of the maximum cumulative decline in market capitalization or fund size for each financial institution during July 2007–December 2008 divided by the market capitalization or total fund size of the institution at the end of June 2007. PCA, Leverage, and systemic risk measures based on Granger causality are calculated over October 2002–September 2005 and July 2004–June 2007. Parameter estimates that are significant at the 5% level are shown in bold.

the recent financial crisis.²⁶

These robustness checks lead us to conclude that, in both sample periods (October 2002–September 2005 and July 2004–June 2007 periods), our results are robust—systemic risk measures based on Granger causality and principal components analysis seem to be early warning signals for the Financial Crisis of 2007–2009.

6.4 Individual Financial Institutions

One final robustness check of our systemic risk measures is to explore their implications for individual financial institutions. In this section we provide a simple comparison between the rankings of individual institutions according to our measures of systemic risk with the rankings based on subsequent financial losses. Consider first the Out-to-Others Granger-causality network measure, estimated over the October 2002–September 2005 sample period. We rank all financial institutions based on this measure, and the 20 highest-scoring institutions are presented in Table 8, along with the 20 highest-scoring institutions based on the maximum percentage loss (Max%Loss) during the crisis period from July 2007 to December 2008.²⁷ We find an overlap of 7 financial institutions between these two rankings.

In Table 7 we showed that in addition to Out-to-Other, Leverage and PCA were also significant in predicting Max%Loss. Therefore, it is possible to sharpen our prediction by ranking financial institutions according to a simple aggregation of all three measures. To that end, we multiply each institution’s ranking according to Out-to-Other, Leverage, and PCA by their corresponding beta coefficients from Table 7, sum these products, and then re-rank all financial institutions based on this aggregate sum. The 20 highest-scoring institutions according to this aggregate measure, estimated using data from October 2002–September 2005, are presented in Table 8. In this case we find an overlap of 12 financial institutions (among the top 20) and most of the rest (among the top 30) with financial institutions ranked on Max%Loss. This improvement in correspondence and reduction in “false positives” suggest that our aggregate ranking may be useful in identifying systemically important entities.

²⁶We omit these results to conserve space, but they are available from the authors upon request.

²⁷The first 11 financial institutions in Max%Loss ranking were bankrupt, therefore, representing the same Max%Loss equalled to 100%.

Out-to-Other	Aggregate Measure	Max Percentage Loss
WELLS FARGO & CO NEW PROGRESSIVE CORP OH BANK OF AMERICA CORP STEWART W P & CO LTD UNITEDHEALTH GROUP INC INVESTMENT TECHNOLOGY GP INC NEW CITIGROUP INC U B S AG FEDERAL NATIONAL MORTGAGE ASSN AMERICAN EXPRESS CO AMBAC FINANCIAL GROUP INC Kingate Global Ltd USD Shares T ROWE PRICE GROUP INC JEFFERIES GROUP INC NEW X L CAPITAL LTD M B N A CORP M B I A INC Graham Global Investment K4D-10 AMERICAN INTERNATIONAL GROUP INC ACE LTD	DEUTSCHE BANK AG U B S AG FEDERAL NATIONAL MORTGAGE ASSN Tomasetti Investment LP LEHMAN BROTHERS HOLDINGS INC C I G N A CORP JEFFERIES GROUP INC NEW CITIGROUP INC INVESTMENT TECHNOLOGY GP INC NEW LINCOLN NATIONAL CORP IN AMERICAN INTERNATIONAL GROUP INC BEAR STEARNS COMPANIES INC ACE LTD C I T GROUP INC NEW WASHINGTON MUTUAL INC RAYMOND JAMES FINANCIAL INC BANK OF AMERICA CORP STEWART W P & CO LTD PROGRESSIVE CORP OH HARTFORD FINANCIAL SVCS GROUP IN	Perry Partners LP EDWARDS A G INC Canyon Value Realization (Cayman) Ltd (A) C I T GROUP INC NEW Tomasetti Investment LP BEAR STEARNS COMPANIES INC ACE LTD LEHMAN BROTHERS HOLDINGS INC WASHINGTON MUTUAL INC Kingate Global Ltd USD Shares FEDERAL HOME LOAN MORTGAGE CORP FEDERAL NATIONAL MORTGAGE ASSN RADIANT GROUP INC AMERICAN INTERNATIONAL GROUP INC AMBAC FINANCIAL GROUP INC STEWART W P & CO LTD M G I C INVESTMENT CORP WIS WACHOVIA CORP 2ND NEW HARTFORD FINANCIAL SVCS GROUP IN X L CAPITAL LTD

Table 8: Granger-causality-network-based measures of systemic risk for a sample of 100 financial institutions consisting of the 25 largest banks, brokers, insurers, and hedge funds (as determined by average AUM for hedge funds and average market capitalization for brokers, insurers, and banks during the time period considered) for the sample period from October 2002 to September 2005. Only the 20 highest-scoring institutions based on Out-to-Other and aggregate measures are displayed. The aggregate measure is an aggregation of the Out-to-Other, Leverage and PCA measures. The maximum percentage loss (Max%Loss) for a financial institution is the dollar amount of the maximum cumulative decline in market capitalization or fund size for each financial institution during July 2007–December 2008 divided by the market capitalization or total fund size of the institution at the end of June 2007. All connections are based on Granger-causal statistics at the 5% level of statistical significance.

7 Conclusion

The financial system has become considerably more complex over the past two decades as distinctions between hedge funds, mutual funds, insurance companies, banks, and broker/dealers have blurred, thanks to financial innovation and deregulation. While such changes are inevitable consequences of prosperity and economic growth, they are accompanied by certain consequences, including the build-up of systemic risk.

In this paper, we propose to measure systemic risk indirectly via econometric techniques such as principal components analysis and Granger-causality tests. These measures seem to capture unique and different facets of systemic risk. Principal components analysis provides a broad view of connections among all four groups of financial institutions, and Granger-causality networks capture the intricate web of statistical relations among individual firms in the finance and insurance industries.

The sheer complexity of the global financial system calls for a multidimensional approach to systemic risk measurement. For example, in a recent simulation study of the U.S. residential housing market, Khandani, Lo, and Merton (2009) show that systemic events can arise from the simultaneous occurrence of three trends: rising home prices, falling interest rates, and increasing efficiency and availability of refinancing opportunities. Individually, each of these trends is benign, and often considered harbingers of economic growth. But when they occur at the same time, they inadvertently cause homeowners to synchronize their equity withdrawals via refinancing, ratcheting up homeowner leverage simultaneously without any means for reducing leverage when home prices eventually fall, ultimately leading to waves of correlated defaults and foreclosures. While excessive risk-taking, overly aggressive lending practices, pro-cyclical regulations, and government policies may have contributed to the recent problems in the U.S. housing market, this study shows that even if all homeowners, lenders, investors, insurers, rating agencies, regulators, and policymakers behaved rationally, ethically, and with the purest of intentions, financial crises can still occur.

Using monthly returns data for hedge-fund indexes and portfolios of publicly traded banks, insurers, and brokers, we show that such indirect measures are indeed capable of picking up periods of market dislocation and distress, and may be used as early warning signals to identify systemically important institutions. Moreover, over the recent sample period, our empirical results suggest that the banking and insurance sectors may be even

more important sources of systemic risk than other parts, which is consistent with the anecdotal evidence from the current financial crisis. The illiquidity of bank and insurance assets, coupled with fact that banks and insurers are not designed to withstand rapid and large losses (unlike hedge funds), make these sectors a natural repository for systemic risk.

The same feedback effects and dynamics apply to bank and insurance capital requirements and risk management practices based on VaR, which are intended to ensure the soundness of individual financial institutions, but may amplify aggregate fluctuations if they are widely adopted. For example, if the riskiness of assets held by one bank increases due to heightened market volatility, to meet its VaR requirements the bank will have to sell some of these risky assets. This liquidation may restore the bank's financial soundness, but if all banks engage in such liquidations at the same time, a devastating positive feedback loop may be generated unintentionally. These endogenous feedback effects can have significant implications for the returns of financial institutions, including autocorrelation, increased correlation, changes in volatility, Granger causality, and, ultimately, increased systemic risk, as our empirical results seem to imply.

As long as human behavior is coupled with free enterprise, it is unrealistic to expect that market crashes, manias, panics, collapses, and fraud will ever be completely eliminated from our capital markets. The best hope for avoiding some of the most disruptive consequences of such crises is to develop methods for measuring, monitoring, and anticipating them. By using a broad array of tools for gauging systemic exposures, we stand a better chance of identifying "black swans" when they are still cygnets.

A Appendix

In this Appendix, we provide the technical details of the linear and nonlinear Granger-causality tests in Sections A.1 and A.2, respectively. Monte carlo simulations for determining the statistical significance of Granger-causality network measures are described in Section A.3.

A.1 Linear Granger Causality

Let X_t and Y_t be two stationary time series and for simplicity assume that they have zero mean. We can represent their linear inter-relationships with the following model:

$$\begin{aligned} X_t &= \sum_{j=1}^m a_j X_{t-j} + \sum_{j=1}^m b_j Y_{t-j} + \epsilon_t, \\ Y_t &= \sum_{j=1}^m c_j X_{t-j} + \sum_{j=1}^m d_j Y_{t-j} + \eta_t, \end{aligned} \tag{A.1}$$

where ϵ_t and η_t are two uncorrelated white noise processes, m is the maximum lag considered, and a_j, b_j, c_j, d_j are coefficients of the model.

The definition of *causality* implies that Y causes X when b_j is different from zero. Likewise X causes Y when c_j is different from zero. When both of these statements are true, there is a feedback relationship between the time series. The model selection criteria of the number of lags considered for the test is based on the Bayesian Information Criterion (see Schwarz, 1978). The causality is based on the F-test of the null hypothesis that coefficients b_j or c_j are equal to zero according to the direction of the Granger causality.

A.2 Nonlinear Granger Causality

Let us assume that $Y_t = (S_t, Z_t)$ is a first-order Markov process (or Markov chain) with transition probabilities:

$$P(Y_t|Y_{t-1}, \dots, Y_0) = P(Y_t|Y_{t-1}) = P(S_t, Z_t|S_{t-1}, Z_{t-1}).$$

Then, all the information from the past history of the process, which is relevant for the transition probabilities in time t , is represented by the previous state of the process, i.e. the state in time $(t - 1)$. Under the additional assumption that transition probabilities do not vary over time, the process is defined as a Markov chain with stationary transition probabilities, summarized in the transition matrix Π .

We can further decompose the joint transition probabilities as follows:

$$\Pi = P(Y_t|Y_{t-1}) = P(S_t, Z_t|S_{t-1}, Z_{t-1}) = P(S_t|Z_t, S_{t-1}, Z_{t-1}) \times P(Z_t|S_{t-1}, Z_{t-1}). \tag{A.2}$$

and thus define the Granger non-causality for a Markov chain as:

Definition 1 *Strong one-step ahead non-causality for a Markov chain with stationary transition probabilities, i.e. Z_{t-1} does not strongly cause S_t given S_{t-1} if:*

$$P(S_t|S_{t-1}, Z_{t-1}) = P(S_t|S_{t-1}) \quad \forall t.$$

Similarly, S_{t-1} does not strongly cause Z_t given Z_{t-1} if:

$$P(Z_t|Z_{t-1}, S_{t-1}) = P(Z_t|Z_{t-1}) \quad \forall t.$$

The Granger non-causality tests in this framework are based on the transition matrix Π that can be represented through the parametrization introduced by Billio and Di Sanzo (2006). The authors show that the transition matrix Π can be represented with a logistic function. More specifically, when we consider two-state Markov chains, the joint probability of S_t and Z_t can be represented as follows:

$$\begin{aligned} P(S_t, Z_t|S_{t-1}, Z_{t-1}) &= P(S_t|Z_t, S_{t-1}, Z_{t-1}) \times P(Z_t|S_{t-1}, Z_{t-1}) \\ &= \frac{\exp(\alpha'V_t)}{1 + \exp(\alpha'V_t)} \times \frac{\exp(\beta'U_t)}{1 + \exp(\beta'U_t)}, \end{aligned} \quad (\text{A.3})$$

where

$$\begin{aligned} V_t &= (1, Z_t)' \otimes (1, S_{t-1})' \otimes (1, Z_{t-1})' \\ &= (1, Z_{t-1}, S_{t-1}, S_{t-1}Z_{t-1}, Z_t, Z_tZ_{t-1}, Z_tS_{t-1}, Z_tZ_{t-1}S_{t-1})', \end{aligned}$$

the vectors α and β have dimensions (8×1) and (4×1) , respectively,

$$U_t = (1, S_{t-1}, Z_{t-1}, Z_{t-1}S_{t-1})' = (1, Z_{t-1})' \otimes (1, S_{t-1})',$$

where \otimes denotes the Kronecker product. U_t is an invertible linear transformation of:

$$U_t^* = [(1 - S_{t-1})(1 - Z_{t-1}), S_{t-1}(1 - Z_{t-1}), (1 - S_{t-1})Z_{t-1}, S_{t-1}Z_{t-1}]',$$

that represents the four mutually exclusive dummies representing the four states of the process at time $t-1$, i.e., $[00, 10, 01, 11]'$. Given this parametrization, the conditions for strong one-step ahead non-causality are easily determined as restrictions on the parameter space.

To impose the Granger non-causality (as in Definition 1), it is necessary that the dependence on S_{t-1} disappears in the second term of the decomposition. Thus, it is simply required that the parameters of the terms of U_t depending on S_{t-1} are equal to zero:

$$H_{S \nRightarrow Z} \quad (S \nRightarrow Z) : \quad \beta_2 = \beta_4 = 0 .$$

Under $H_{S \nrightarrow Z}$, S_{t-1} does not strongly cause one-step ahead Z_t given Z_{t-1} . The terms S_{t-1} and $S_{t-1}Z_{t-1}$ are excluded from U_t , hence $P(Z_t|S_{t-1}, Z_{t-1}) = P(Z_t|Z_{t-1})$.

Both hypotheses can be tested in a bivariate regime-switching model using a Wald test or a Likelihood ratio test. In the empirical analysis, bivariate regime-switching models have been estimated by maximum likelihood using the Hamilton’s filter (Hamilton (1994)) and in all our estimations we compute the robust covariance matrix estimators (often known as the sandwich estimator) to calculate the standard errors (see Huber (1981) and White (1982)).

A.3 Monte Carlo Simulation Experiments

To test our procedure in identifying Granger-causal linkages, we perform a simple Monte Carlo simulation experiment. Because we wish to retain the contemporaneous dependence structure among the individual time series, our working hypothesis is that the dependence arises from a common factor, i.e., the S&P 500. Specifically, to simulate 100 time series (one for each financial institution), we start with the time-series data for these institutions and filter out heteroskedastic effects with a GARCH(1,1) process, as in the linear Granger-causality analysis of Section 5.2. Then we regress the residuals on the returns of the S&P 500 index:

$$y_i = \alpha_i + \beta_i \text{S\&P500} + \sigma_i \epsilon_i \quad , \quad i = 1, \dots, 100 \quad , \quad \epsilon_i \text{ IID } \mathcal{N}(0, 1)$$

and store the parameter estimates $\hat{\alpha}_i$, $\hat{\beta}_i$, and $\hat{\sigma}_i$, to be used to calibrate our simulation’s data-generating process, where “IID” denotes independently and identically distributed random variables.

Next, we simulate 36 monthly returns (corresponding to the 3-year period in our sample) of the common factor and the residual returns of the 100 hypothetical financial institutions. Returns of the common factor come from a normal random variable with mean and standard deviation set equal to that of the S&P 500. The residuals ϵ_{ij} are IID standard normal random variables. We repeat this simulation 500 times and obtain the resulting population of our simulated series:

$$y_{ji}^S = \hat{\alpha}_i + \hat{\beta}_i \text{S\&P500}_j^S + \hat{\sigma}_i \epsilon_{ji}^S \quad , \quad i = 1, \dots, 100 \quad , \quad j = 1, \dots, 500. \quad (\text{A.4})$$

For each j , we perform our Granger-causality analysis and calculate the number of significant connections, and compute the empirical distribution of the various test statistics which can then be used to assess the statistical significance of our empirical findings.

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