Measuring Systemic Risk in the Finance and Insurance Sectors*

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A significant contributing factor to the Financial Crisis of 2007–2009 was the apparent interconnectedness among hedge funds, banks, brokers, and insurance companies, which amplified shocks into systemic events. In this paper, we propose five measures of systemic risk based on statistical relations among the market returns of these four types of financial institutions: correlations, cross-autocorrelations, principal components analysis, regime-switching models, and Granger-causality tests. We find that all four sectors have become highly interrelated and less liquid 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 while hedge funds can provide early indications of market dislocation, their contributions to systemic risk may not be as significant as those of banks, insurance companies, and brokers who take on risks more appropriate for hedge funds.

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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 five 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. Our measures are based on: (1) correlations; (2) return illiquidity; (3) principal components analysis; (4) regime-switching models; and (5) Granger-causality tests. They are motivated by the kind of events that created so much market dislocation in August 1998 and the Financial Crisis of 2007–2009, and are meant to capture the "four L's" of systemic risk—liquidity, leverage, linkages, and losses.

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.

[1]For 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.

The theoretical underpinnings and institutional mechanisms by which correlation, illiquidity, and sudden changes in regime combine to produce systemic risk have become clearer.[2] Because many financial institutions make use of leverage, their positions are often considerably larger than the amount of collateral posted to support those positions. 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 that 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 over the past three years. In particular, the more illiquid the positions, the larger the price impact of forced liquidations, leading to a series of insolvencies and defaults, and recessionary pressures on the real economy as financial institutions withdraw credit.

The likelihood of a major dislocation also 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.

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,

[2]See, 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).

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 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 just 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 regime-switching 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 are reported in Section 5. We conclude in Section 6.

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 though which these spirals can spreads 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 Nicolo 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 sim-

ple 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. The authors explained the time-varying CoVaR and VaR measures of these financial institutions using market returns, the slope of the yield curve, aggregate credit spread, and implied equity-market volatility based on the VIX index. They also estimated contemporaneous interdependencies, i.e., how the VaR of an institution changes, conditional on the VaR of other institutions. 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.

3 Systemic Risk Measures

In this section we summarize our five measures of systemic risk, which are all designed to capture aspects of changes in liquidity, expected returns, and correlation.

Illiquidity, correlation, and systemic risk are tightly linked.[3] The more illiquid the portfolio, the larger the price impact of a forced liquidation, which erodes the investor's risk capital that much more quickly. If many investors face the same "death spiral" at the same time, i.e., if they become more highly correlated during times of distress, and if those investors are obligors of a small number of major financial institutions, then small market movements can cascade quickly into a global financial crisis. This in effect explains the essence of the systemic risk. Besides illiquidity, the likelihood of a major dislocation also depends on the concentration of risks among financial institutions, how closely connected those institutions are with each other and with the rest of the economy, how sensitive they are to changes in market prices and economic conditions, and the degree of correlation among the holdings of financial institutions.

In Section 3.1 we review Getmansky, Lo, and Makarov's (2004) argument for serial correlation as a measure of illiquidity. In Section 3.2, we propose principal components analysis as a means of capturing increased correlation among our four indexes. Section 3.3 summarizes the regime-switching model we use to detect shifts in the statistical properties of our index returns, and Section 3.4 describes the Granger-causality tests we use to determine the directionality of correlation among our indexes.

3.1 Illiquidity and Correlation

To gauge the illiquidity risk exposure of a given financial institution, Lo (2002) and Getmansky, Lo, and Makarov (2004) suggest using the autocorrelation coefficients ρ_k of the institution's monthly returns, where $\rho_k \equiv \text{Cov}[R_t, R_{t-k}]/\text{Var}[R_t]$ is the k-th order autocorrelation of $\{R_t\}$,[4] which measures the degree of correlation between month t's return and month $t-k$'s return. To see why autocorrelations may be useful indicators of liquidity ex-

[3] Diamond and Rajan (2005) show that through exacerbating aggregate liquidity shortages bank failures can lead to a contagion of failures and systemic risk.

[4] The k-th order autocorrelation of a time series $\{R_t\}$ is defined as the correlation coefficient between R_t and R_{t-k}, which is simply the covariance between R_t and R_{t-k} divided by the square root of the product of the variances of R_t and R_{t-k}. But since the variances of R_t and R_{t-k} are the same under the assumption of stationarity, the denominator of the autocorrelation is simply the variance of R_t.

posure, recall that one of the earliest financial asset pricing models is the martingale model, in which asset returns are serially uncorrelated ($\rho_k = 0$ for all $k \neq 0$). Indeed, the title of Samuelson's (1965) seminal paper—"Proof that Properly Anticipated Prices Fluctuate Randomly"—provides a succinct summary for the motivation of the martingale property: In an informationally efficient market, price changes must be unforecastable if they are properly anticipated, i.e., if they fully incorporate the expectations and information of all market participants.

This extreme version of market efficiency is now recognized as an idealization that is unlikely to hold in practice.[5] In particular, market frictions such as transactions costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on shortsales and other trading practices do exist. Clearly, such frictions contribute to the possibility of serial correlation in asset returns that cannot easily be "arbitraged" away. From this perspective, the degree of serial correlation in an asset's returns can be viewed as a proxy for the magnitude of the frictions, and illiquidity is one of most common forms of such frictions.

A more prosaic reason for using serial correlation as a proxy for liquidity is return-smoothing. Consider a hedge-fund manager holding a portfolio of illiquid securities, i.e., securities that are not frequently traded and for which well-established market prices do not exist. Such a hedge-fund manager has considerable discretion in marking the portfolio's value at the end of each month to arrive at the fund's net asset value. Given the nature of hedge-fund compensation contracts and performance statistics, managers have an incentive to "smooth" their returns by marking their portfolios to less than their actual value in months with large positive returns so as to create a "cushion" for those months with lower returns. Such return-smoothing behavior yields a more stable set of returns over time, with lower volatility and, therefore, a higher Sharpe ratio, but it also produces serial correlation as a side effect. Of course, if the securities in the manager's portfolio are actively traded, the manager has little discretion in marking the portfolio; it is "marked to market". The more illiquid the portfolio, the more discretion the manager has in marking its value and smoothing returns, creating serial correlation in the process.[6] The impact of smoothed

[5] See, for example, Farmer and Lo (2000) and Lo (2004).

[6] There are, of course, other explanations for serial correlation in portfolio returns, of which return-smoothing is only one. Others include nonsynchronous trading, time-varying expected returns, and market inefficiencies.

returns and serial correlation is considered in more detail in Lo (2002), Getmansky, Lo, and Makarov (2004), and Khandani and Lo (2009).

Moreover, as shown by Battiston et al. (2009), in a framework where financial institutions have excessive leverage and belong to a network based on credit exposures, individual financial fragility can feed on itself, leading to a systemic shock. If such a shock is large enough so that several creditors withdraw part or all of their credit simultaneously, obligors may be forced to liquidate at least part of their positions, to satisfy their creditors. The more illiquid are the assets to be liquidated, the more likely will such forced unwinds result in a spiral of losses that generate financial crisis. Serial correlation can proxy for illiquidity, and may therefore serve as an indirect measure of this exposure.

3.2 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

$$R_{jt} \;=\; \alpha_j \;+\; \delta_1 F_{1t} \;+\; \cdots \;+\; \delta_K F_{Kt} \;+\; \epsilon_{jt} \tag{1}$$

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

$$\mathrm{Var}[\mathbf{R}_t] \;\equiv\; \mathbf{\Sigma} \;=\; \mathbf{Q}\mathbf{\Theta}\mathbf{Q}' \qquad , \qquad \mathbf{\Theta} \;=\; \begin{bmatrix} \theta_1 & 0 & \cdots & 0 \\ 0 & \theta_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & 0 & \theta_N \end{bmatrix} \tag{2}$$

where $\mathbf{\Theta}$ contains the eigenvalues of $\mathbf{\Sigma}$ along its diagonal and $\mathbf{Q}$ is the matrix of corresponding eigenvectors. Since $\mathbf{\Sigma}$ 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 $\mathbf{\Sigma}$ 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 $\mathbf{\Sigma}$.

The only challenge is the fact that the covariance matrix $\mathbf{\Sigma}$ must be estimated, hence we encounter the well-known problem that the standard estimator

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

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.[7] 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.

3.3 Regime-Switching Models

Our next measure of systemic risk is motivated by sudden regime-shifts in the expected returns and volatilities of financial institutions. The Mexican peso crisis of 1994–1995, the Asian crisis of 1997, the global flight to quality precipitated by the default of Russian GKO debt in August 1998, and the financial crisis of 2007–2009 are all examples of regime shifts. Linear models are generally incapable of capturing such discrete changes. We propose to model such shifts by a regime-switching process in which two states of the world are hypothesized, and the data are allowed to determine the parameters that characterize each state, as well as the likelihood of transitioning from one to the other. Regime-switching models have been used in a number of contexts, ranging from Hamilton's (1989) model of the business cycle to Ang and Bekaert's (2004) regime-switching asset allocation model. We propose to estimate a simple two-state Markov regime-switching model for the bank, hedge fund, insur-

[7] Singularity 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.

ance, and broker indexes to obtain another measure of systemic risk, i.e., the possibility of switching from a normal to a distressed regime.[8] In particular, let index returns $R_{i,t}$ satisfy the following stochastic process:

$$R_{i,t} \;=\; \mu_i(Z_{i,t}) \;+\; \sigma_i(Z_{i,t})u_{i,t} \tag{3}$$

where $R_{i,t}$ is the excess return of index i in period t, σ_i is the volatility of index i, $u_{i,t}$ is independently and identically distributed (IID) over time, and $Z_{i,t}$ is a two-state Markov chain with transition probability matrix $\mathbf{P}_{z,i}$ for index i. By convention and without loss of generality, $Z_{i,t}=0$ when index i is in the low-volatility regime, and $Z_{i,t}=1$ when index i is in the high-volatility regime.

The joint probability of high-volatility regimes (when $Z_{i,t}=1,\ i=1,\ldots,4$) for all indexes captures stress periods characterized by high volatility for all four types of financial institutions and can be another measure of systemic risk. To estimate this joint probability without restricting the dependence among the four return indexes, we require $2^4=16$ distinct regimes which is clearly infeasible given the length of our time series. For simplicity, we estimate the probability of being in the high-volatility regime for each index i separately, and then compute the joint probability as the product of these univariate estimates, implicitly assuming conditional independence:

$$J_{p,t} \;=\; \prod_{i=1}^{m} \text{Prob}\,(Z_{i,t}=1|\mathcal{R}_{i,t}), \tag{4}$$

where $\mathcal{R}_{i,t} \equiv (R_{i,t}, R_{i,t-1}, \ldots, R_{i,1})$. To the extent that periods of high volatility are positively dependent among the four indexes, (4) will be a conservative measure, under-estimating the true probability of a joint event.[9]

[8]The importance of using regime-switching models is well established in the financial economics literature. Examples are found in Bekaert and Harvey's (1995) regime-switching asset pricing model, Ang and Bekaert's (2002) and Guidolin and Timmermann's (2008) regime-switching asset allocation models, Lettau, Ludvigson, and Wachter's (2008) regime-switching equity premia model, Bollen, Gray and Whaley's (2000) analysis of regimes in currency options, and Billio and Pelizzon's (2000, 2003) analysis of VaR calculation, volatility spillover, and contagion among markets. Moreover, regime-switching models have been successfully applied to constructing trading rules in equity markets (Hwang and Satchell, 2007), equity and bond markets (Brooks and Persand, 2001), hedge funds (Chan et al., 2006, and Billio, Getmansky, and Pelizzon, 2009), and foreign exchange markets (Dueker and Neely, 2004).

[9] To see why, observe that for any two events E_1 and E_2, the joint probability $\text{Prob}\,(E_1 \cap E_2)$ is equal to $\text{Prob}\,(E_1|E_2)\text{Prob}\,(E_2)$ by definition. If the two events are positively dependent, then $\text{Prob}\,(E_1|E_2) >$

The independence of the four return indexes can be tested explicitly by comparing $J_{p,t}$ to the product of the following unconditional probabilities:

$$A_{p,t} = \prod_{i=1}^{m} \pi_{i,1} \tag{5}$$

where:

$$\pi_{i,1} \equiv \frac{(1 - p_{i,11})}{(2 - p_{i,00} - p_{i,11})} \tag{6}$$

is the unconditional probability of being in state 1 for index i and $p_{i,jj}$ is a diagonal entry of the transition matrix $P_{z,i}$ and represents the conditional probability that $Z_{i,t}=j$, conditional on $Z_{i,t-1} = j,\ j = 0, 1$. The larger the difference between $J_{p,t}$ and $A_{p,t}$, the larger is the interdependence of these financial sectors.

In summary, we infer greater interdependence among the four sectors when we observe a significant increase in the joint probability of a high-volatility regime, i.e., a large $J_{p,t}$. This increase can be due either to contagion effects or to the possibility that the four financial institution sectors are all exposed to the same common factor. Both of these relationships capture an aspect of systemic risk.

Another aggregate measure of systemic risk is $S_{p,t}$—simply the average of all probabilities of high-volatility regimes among all financial institutions:

$$S_{p,t} = \frac{1}{m} \sum_{i=1}^{m} \text{Prob}\left(Z_{i,t} = 1 | R_{i,t}\right) . \tag{7}$$

As before, we identify the presence of interdependence between all financial institutions when we observe a significant increase in the average probability $S_{p,t}$ of high-volatility regimes.

3.4 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

Prob (E_1), i.e., the occurrence of E_2 implies a higher probability of E_1 occurring than the unconditional probability of E_1. But this implies that Prob $(E_1 \cap E_2) >$ Prob (E_1)Prob (E_2), hence the product is a conservative estimate of the joint probability.

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 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 banks and hedge funds, and let ZH_t and ZB_t be Markov chains that characterize the expected returns and volatilities of the two indexes, respectively. The general case of the nonlinear Granger-causality estimation is considered in the Appendix. We can test the nonlinear causal interdependence between these two series by testing the following hypotheses:

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:

$$P(Y_t \,|\, Y_{t-1}) \quad = \quad P(ZH_t, ZB_t \,|\, ZH_{t-1}, ZB_{t-1}) \; . \tag{8}$$

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 $\boldsymbol{P}$. We can then decompose the joint transition probabilities as:

$$\begin{aligned} P(Y_t|Y_{t-1}) \quad &= \quad P(ZH_t, ZB_t \,|\, ZH_{t-1}, ZB_{t-1}) & (9) \\ &= \quad P(ZB_t \,|\, ZH_t, ZH_{t-1}, ZB_{t-1}) \times P(ZH_t \,|\, ZH_{t-1}, ZB_{t-1}) \; . & (10) \end{aligned}$$

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:

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

by decomposing the joint probability:

$$\begin{aligned} P(ZH_t, ZB_t \,|\, ZH_{t-1}, ZB_{t-1}) \quad &= \quad P(ZH_t \,|\, ZB_t, ZH_{t-1}, ZB_{t-1}) \times \\ & \qquad P(ZB_t \,|\, ZH_{t-1}, ZB_{t-1}) \; . \end{aligned} \tag{11}$$

In this case, the last term becomes

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

2. Granger Non-Causality from ZB_t to ZH_t:

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

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).

To develop a better understanding of the dynamics within the hedge-fund industry, especially the differences between liquid and illiquid strategies, we consider four hedge-fund indexes: "Global Macro", "Long/Short Equity", "Liquid", and "Illiquid" indexes, with the latter two defined as asset-weighted indexes of strategies with first-order return autocorrelations ρ_1 less than and equal to or greater than 0.30, respectively (see Getmansky, Lo, and Makarov, 2004). Global Macro and Long/Short Equity are separated from the Liquid index despite the fact that their return autocorrelations are 0.10 and 0.22, respectively, primarily because of their market shares: the former accounts for 24.9% of hedge-fund assets

under management (AUM) in the TASS database and the latter accounts for 29.3%. Using our classification rule, the Illiquid hedge-fund index is an asset-weighted average of the CS/Tremont Convertible Bond Arbitrage, Emerging Markets, Event Driven, Fixed Income, and Multi-Strategy indexes (with an average ρ_1 of 0.45), while the Liquid hedge-fund index is an asset-weighted average of Dedicated Shortseller, Equity Market Neutral, and Managed Futures indexes (with an average ρ_1 of 0.03). The Illiquid strategies comprise 37.9% of the sample, while Liquid ones comprise 7.9%.

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).

The annual mean and standard deviations for Global Macro and Long/Short hedge-fund strategies are 12.36% (10.57%) and 9.83% (10.22%), respectively. Both strategy indexes are

highly liquid, with first order autocorrelation coefficients of 0.10 and 0.22, respectively. The first-order autocorrelation coefficient for the Illiquid index is 0.45, while the Liquid index has a first-order autocorrelation of only 0.03.[10] The performance and volatility of the Liquid and Illiquid indexes are similar over the sample period. The Illiquid index comprises 37.9% of the sample as measured by assets under management (AUM), while Liquid index comprises 7.9%. Of course, both Global Macro (which is 24.9% of the sample) and Long/Short Equity (which is 29.3% of the sample) are liquid strategy indexes that are considered separately from the Liquid index, which explains the low proportion of the Liquid index in the sample.

In the early part of the sample (1994–1996), the TASS hedge-fund database (and perhaps the industry) was dominated by Global Macro funds, which consisted of more than 50% of the total AUM in the database. Over time, its relative importance has declined, now accounting for only 10% of TASS AUM. Also, the Global Macro index volatility was 14% during the first part of the sample (1994–1996, just prior to the Asian crisis), whereas average Hedge Fund volatility was 7.96% during that same period. As a result, the first part of the sample of Hedge Fund returns exhibits higher volatility than later periods.

We also construct a 0/1 indicator variable that delineates "crisis periods", taking the value 1 during the following periods (see Rigobon, 2003): the Mexican crisis (December 1994 to March 1995); the Asian crisis (June 1997 to January 1998); the Russian default and LTCM crisis (August 1998 to October 1998); the Brazilian crisis (January 1999 to February 1999); the Internet Crash (March 2000 to May 2000); the Argentinean crisis (October 2000 to December 2000); September 11, 2001; the disappearance of merger activities, the increase in defaults and bankruptcies, and the accounting problems of WorldCom, Enron, etc. (June 2002 to October 2002); the Subprime Mortgage Crisis or 2007 (August 2007 to January 2008), and the Global Financial Crisis of 2008 (September 2008 - November 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 illiquidity and correlation measures, Section 5.2 contains the

[10]The November 2008 Equity Market Neutral index was severely impacted by the Madoff fraud (the index apparently had a large weight to Fairfield Sentry), with a monthly return of -40%. To ensure that our results are not driven by this single event, CS/Tremont has recomputed the index excluding all Madoff funds, in which case the November 2008 return becomes -0.06%.

Statistic	Hedge Funds	Brokers	Banks	Insurers	S&P500	Global Macro	Long Short Equity	Illiquid Funds	Liquid Funds
Sample Size	180	180	180	180	180	180	180	180	180
Ann. Mean (%)	8.72	14.22	10.12	7.90	8.59	12.36	9.83	7.25	7.13
Ann. SD (%)	7.96	29.05	19.37	17.84	15.17	10.57	10.22	6.52	6.25
Min (%)	-7.55	-31.56	-22.38	-24.09	-16.64	-11.55	-11.43	-10.07	-7.22
Max (%)	8.53	26.75	14.26	23.67	9.84	10.60	13.01	4.87	7.60
Median (%)	0.79	1.64	1.40	0.97	1.26	1.14	0.81	0.86	0.51
Skewness	-0.17	-0.41	-0.94	-0.47	-0.75	-0.03	0.02	-1.93	-0.28
Kurtosis	5.26	3.99	5.64	7.56	4.27	5.93	6.40	10.85	5.85
ρ1	0.22	0.13	0.02	0.08	0.10	0.10	0.22	0.45	0.03
p-value(ρ1)	0.00	0.07	0.80	0.30	0.17	0.20	0.00	0.00	0.69
ρ2	0.11	-0.09	-0.01	0.02	-0.01	0.04	0.10	0.24	-0.18
p-value(ρ2)	0.13	0.22	0.88	0.80	0.90	0.63	0.20	0.00	0.02
ρ3	0.04	0.03	-0.01	-0.05	0.07	0.09	-0.03	0.10	-0.07
p-value(ρ3)	0.61	0.73	0.93	0.54	0.35	0.23	0.73	0.18	0.38

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. For comparison, summary statistics for four hedge-fund indexes are included: the CS/Tremont Global Macro index, the CS/Tremont Long-Short Equity index, an asset-weighted index of Illiquid hedge-fund strategies (Convertible Bond Arbitrage, Emerging Markets, Event Driven, Fixed Income, and Multi-Strategy), and an asset-weighted index of Liquid hedge-fund strategies (Dedicated Shortseller, Equity Market Neutral, and Managed Futures).

results of PCA applied to the return indexes, Section 5.3 provides regime-switching model estimates, and Section 5.4 reports the outcomes of linear and nonlinear Granger-causality tests. To better understand the implications of these Granger-causality relationships, in Section 5.5 we present results for individual financial institutions and simple visualizations via network diagrams. And in Section 5.6, we evaluate the predictive power of Granger causality relationships.

5.1 Illiquidity and Correlation

Following the methodology of Section 3, we use the first-order return autocorrelation coefficient ρ_1 as an illiquidity measure. For all four financial institution indexes we calculate 36-month rolling-window first-order autocorrelations over the entire sample period (hence adjacent autocorrelation coefficients have 35 monthly returns in common). The results of rolling-window autocorrelations for Hedge Funds, Brokers, Banks, and Insurers are presented in Figure 1.

We can see from Figure 1 that the autocorrelation coefficients vary considerably over

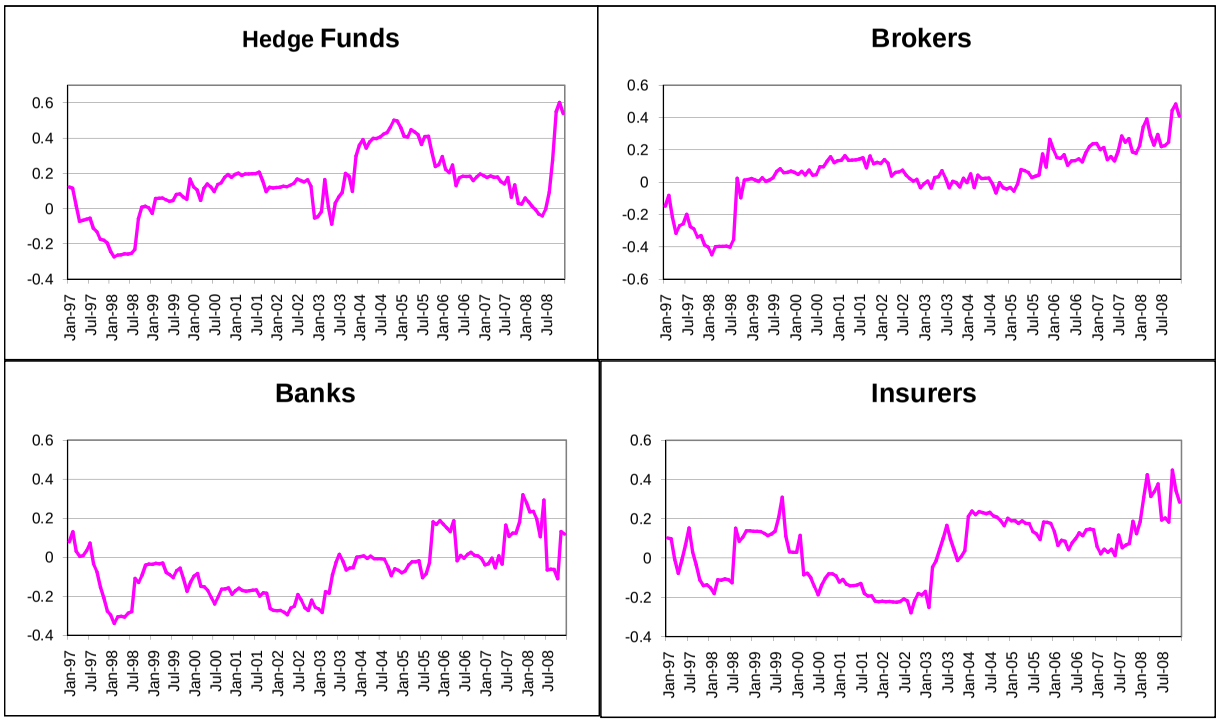


Figure 1: 36-month rolling-window autocorrelation coefficients for Hedge Funds, Brokers, Banks, and Insurers from January 1994 to December 2008.

time. Starting in 2004, all financial institutions became positively autocorrelated. For all financial institutions, this illiquidity measure sharply increased during the two liquidity crises: LTCM 1998 and the Financial Crisis of 2007–2009. Hedge Fund autocorrelations increased significantly from January 2003 to January 2005, foreshadowing the beginning of a crisis in the hedge fund industry that started in 2005 due to the General Motors (GM) downgrade, high leverage in the hedge fund industry, and problems in the convertible bond market. During the 2005–2007 period, Hedge Fund return autocorrelations sharply decreased, most likely due to hedge funds unwinding their positions and systematically reducing their risk.[11] However, during the 2008 crisis the autocorrelation jumped precipitously, almost doubling in October 2008 from 0.28 to 0.55. The autocorrelation of the Broker index was negative during the beginning of the sample period (October 1997 to July 1998), increasing afterwards during the 1998 LTCM event, and increasing monotonically until March 2008 (0.40) and October 2008 (0.44). Similar to the Broker index, the autocorrelation coefficients of the Bank index jumped to 0.23 in March 2008 and then subsided during the second half of the 2008. The autocorrelations of the Insurer index peaked in September 1999 (0.31), March 2008 (0.42), and October 2008 through the end of the sample (0.40).

In conclusion, it seems that all financial institutions experienced high autocorrelation, i.e., illiquidity, during specific liquidity crises such as 1998 and 2007–2009. For example, during the most recent crisis many financial institutions were exposed to highly illiquid mortgage-backed securities and credit derivatives. In contrast, during the Internet Crash of 2000, financial institutions were mostly invested in liquid exchange-traded stocks, and we do not observe an increase in autocorrelation measure during this crisis. Also, we show that the increase in autocorrelation from negative to positive first began in 2004 for all financial institutions, indicating a build-up in illiquidity several years before the Financial Crisis of 2007–2009.

To develop an aggregate indicator of illiquidity in the hedge-fund industry, we construct a time series of asset-weighted average autocorrelations of all hedge funds in the TASS/Tremont database with at least 36 trailing months of non-missing returns (with which we estimate each fund's rolling-window autocorrelations). Figure 2 plots this average from January 1982 to December 2008, along with the cross-sectional median autocorrelations

[11] This period overlapped with the Federal Reserve's increase in interest rates in 2004–2006. During this time, many financial institutions deleveraged.

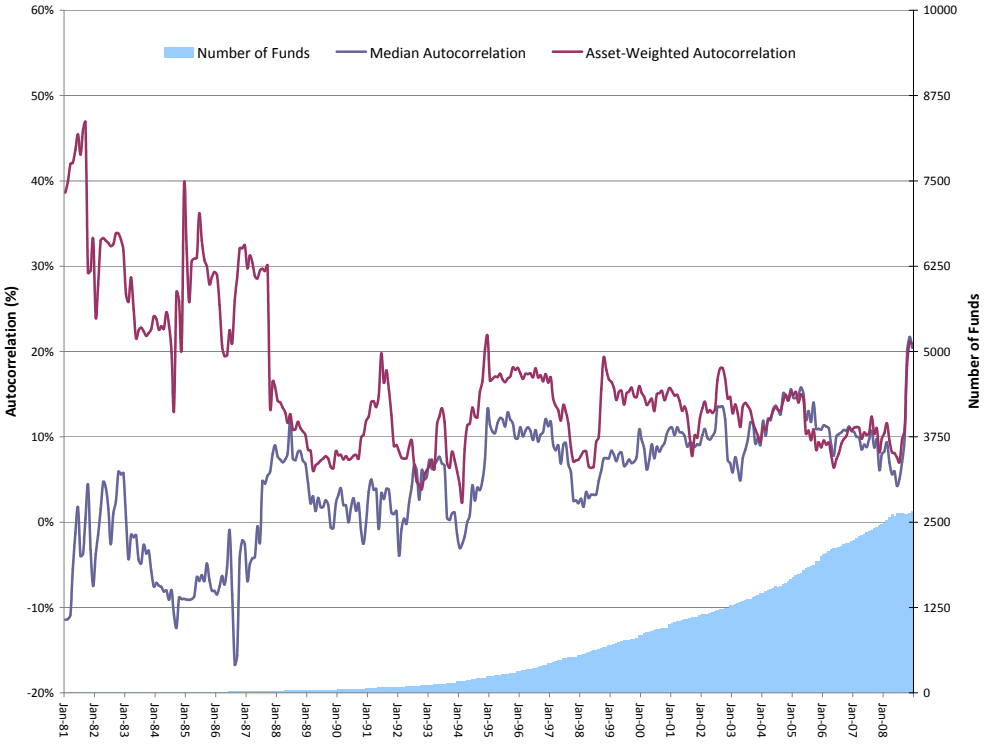


Figure 2: Monthly cross-sectional medians and asset-weighted autocorrelation coefficients of individual hedge funds, and the total number of funds in the TASS Combined hedge-fund database with at least 36 consecutive trailing months of returns, from January 1981 to December 2008.

and, at the bottom of the figure, the total number of hedge funds in the database. The median correlation is quite different from the asset-weighted correlation in the earlier part of the sample, but as the number of funds increases over time, the behavior of these two correlation measures converges. Figure 2 shows considerable time-variation in the average autocorrelations, with dynamics that seem to be related to liquidity events. For example, between November 1980 and July 1982, the S&P 500 dropped 23.8%; in October 1987 the S&P 500 fell by 21.8%; in 1990, the Japanese "bubble economy" burst; in August 1990, the Persian Gulf War began with Iraq's invasion of Kuwait, ending in January 1991 with Kuwait's liberation by coalition forces; in February 1994, the U.S. Federal Reserve started a tightening cycle that caught many hedge funds by surprise, causing significant dislocation in bond markets worldwide; the end of 1994 witnessed the start of the "Tequila Crisis" in Mexico; in August 1998, Russia defaulted on its government debt; and between August 2000 and September 2002, the S&P 500 fell by 46.3%; and the recent Subprime Mortgage Crisis of 2007 and the Global Financial Crisis of 2008 when the S&P 500 decreased by 38.5%, the largest decline since the 38.6% plunge in 1937. In each of these cases, the weighted autocorrelation rose in the aftermath, and in most cases abruptly. Since we are using a 36-month rolling window, as outliers drop out, correlations can shift suddenly. However, as a coarse measure of liquidity in the hedge-fund sector, the weighted autocorrelation is intuitively appealing and informative.

Another simple indicator of systemic risk is correlation among financial institutions, hence we compute the six pairwise correlations between our four return indexes using 36-month rolling windows. We find that the correlations between the return indexes for Hedge Funds and Brokers are high throughout the sample, generally ranging from 0.4 to 0.8. The same is true for correlations between the return indexes for Banks and Insurers, with correlations ranging from 0.5 to 0.9. These persistent high correlations are plausible given the various business relationships and similarities among these institutions. Hedge funds obtain leverage, clear trades, and borrow stock from brokers. Brokers often trade with their own accounts by implementing strategies similar to hedge funds. And banks and insurance companies often engage in similar activities, providing loans and guarantees to their clients in highly regulated settings where assets must be carefully matched to liabilities.

The correlation coefficients for all pairs depicted in Figure 3 increased sharply before and during the two liquidity crises, 1998 and 2007–2009. In contrast, the correlations between

the return indexes for Brokers and Banks, Brokers and Insurers, Hedge Funds and Banks, and Hedge Funds and Insurers decreased precipitously in 2000–2003. After 2003, all correlations increased. There are many different factors that could have generated the increase in correlations after 2003. One of them could be the gradual increase in interest rates by the Federal Reserve starting in June 2004, leading many financial institutions to de-leverage their positions during this period. Another factor could be the general reduction in volatility. We find that even after controlling for the change in volatility using a GARCH(1,1) model, we still observe an increase in correlation after 2003.[12] After the Subprime Crisis of 2007, the correlation between Hedge Funds and Banks decreased, possibly the result of hedge funds deleveraging and reducing risk exposures, but the correlation increased again in September 2008.[13]

A shock to the system can lead to forced liquidations of positions across all financial institutions, and since many of these entities rely on leveraged positions in illiquid assets, shocks can quickly become systemic events. In summary, both autocorrelation and correlation among financial institutions serve as useful systemic risk measures.

We also compute return correlations between financial institutions at higher leads and lags, and the results are presented in Figure 4. To detect lead/lag relationships among the indexes, we compute cross-autocorrelations for lag i, i.e., $\text{Corr}[X_{t-i}, Y_t]$). We find that Hedge Funds are significantly correlated (at the 5% level) with the first and second lags of Brokers and Banks, but only with the second lag of Insurers. This finding could be related to contagion from financial institutions to hedge funds. However, this correlation may also be related to the increased autocorrelation of Hedge Fund returns (see Figure 1). However, even if we adjust for the autocorrelation of Hedge Fund returns, we still find contagion from all financial institutions to Hedge Funds.[14] Banks and Insurers are correlated with the lag-5 returns of Brokers. We repeat this analysis for the 2001–2008 period to focus on the more recent crises, and the results are qualitatively consistent except that only the first lags of Brokers, Banks, and Insurers are significantly correlated with the current returns of Hedge Funds. In conclusion, shocks to Brokers, Banks, and Insurers affect Hedge Fund returns, but the effect is not symmetric, i.e., shocks to Hedge Funds do not propagate to other financial

[12]Results are available from the authors upon request.

[13]We also control for heteroskedasticity in calculating correlations among financial institutions using a GARCH(1,1) model and the results are similar. The magnitudes of the correlations change, but the dynamics are the same. The results are available from the authors upon request.

[14]Results are available from the authors upon request.

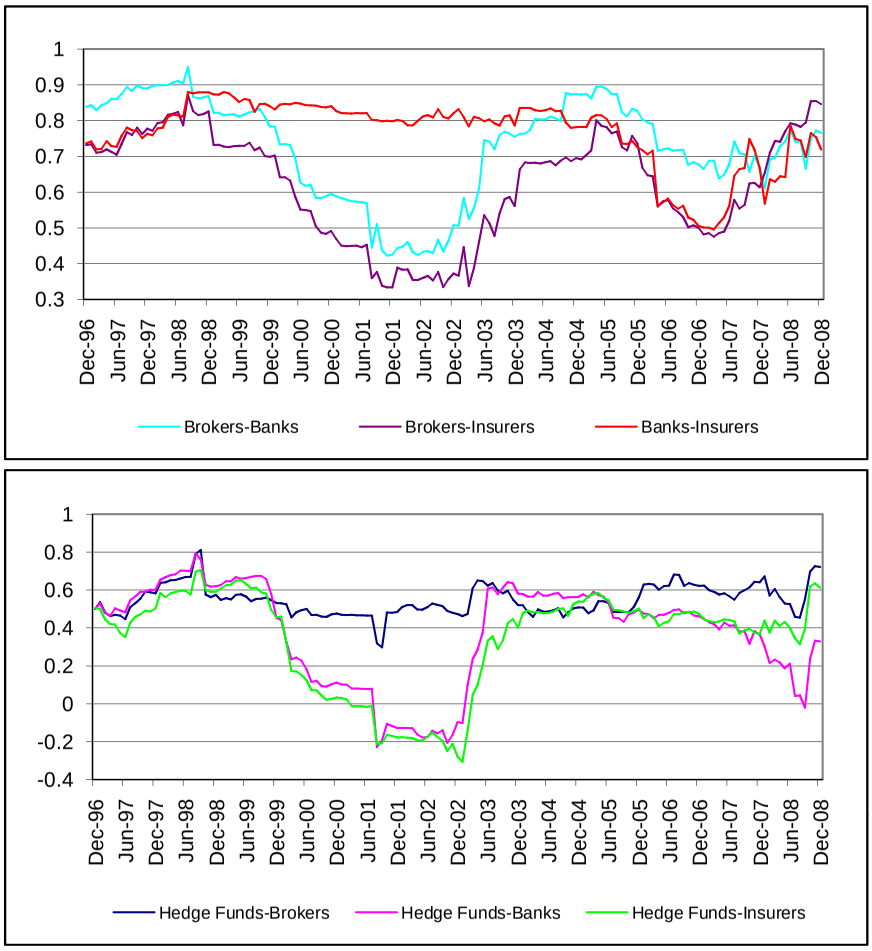


Figure 3: 36-month rolling-window pairwise correlations among monthly return indexes of Banks, Brokers, Insurers, and Hedge Funds.

institutions as readily.

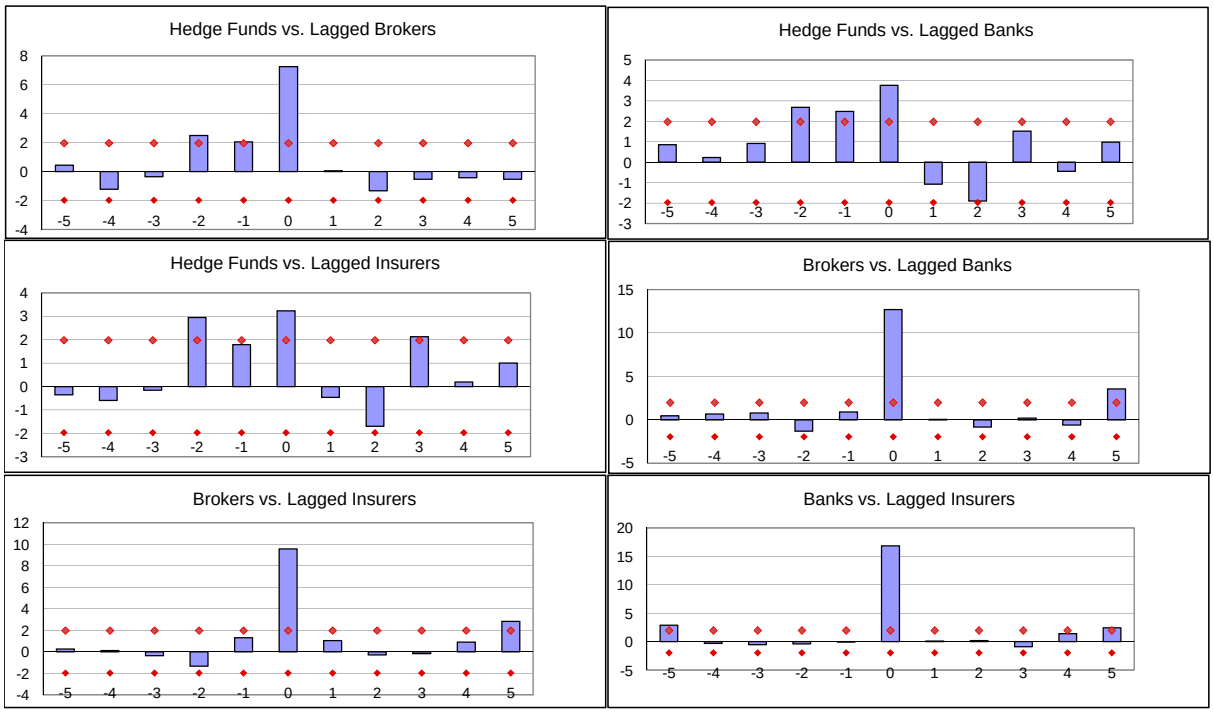


Figure 4: Contemporaneous and lagged pairwise correlations among monthly return indexes of Banks, Brokers, Insurers, and Hedge funds, from January 1994 to December 2008. Red dots indicate 95% confidence intervals.

Correlations among the four hedge-fund indexes (Global Macro, Long/Short Equity, Illiquid, and Liquid indexes) are presented in Table 2 for the two samples 1994–2000 and 2001-2008. We also compute six pairwise correlations between these four hedge-fund return indexes using 36-month rolling windows. The results are presented in Figure 5. Similar to correlations between financial institutions, the correlations between all four hedge-fund sectors started to increase in 2003 and have increased steadily through the end of the sample which is characterized by the turbulent 2007–2009 period. The correlation between Illiquid and Liquid indexes is the lowest throughout the sample and is not significantly different from zero.

Interestingly, Long/Short Equity, which is a fairly liquid strategy (its first-order autocorrelation coefficient is 0.22) is uncorrelated with the Liquid index in the first part of the sample, but this correlation increases steadily after 2003. However, the Long/Short Equity strategy is highly correlated with the Illiquid index during the whole time period. Moreover,

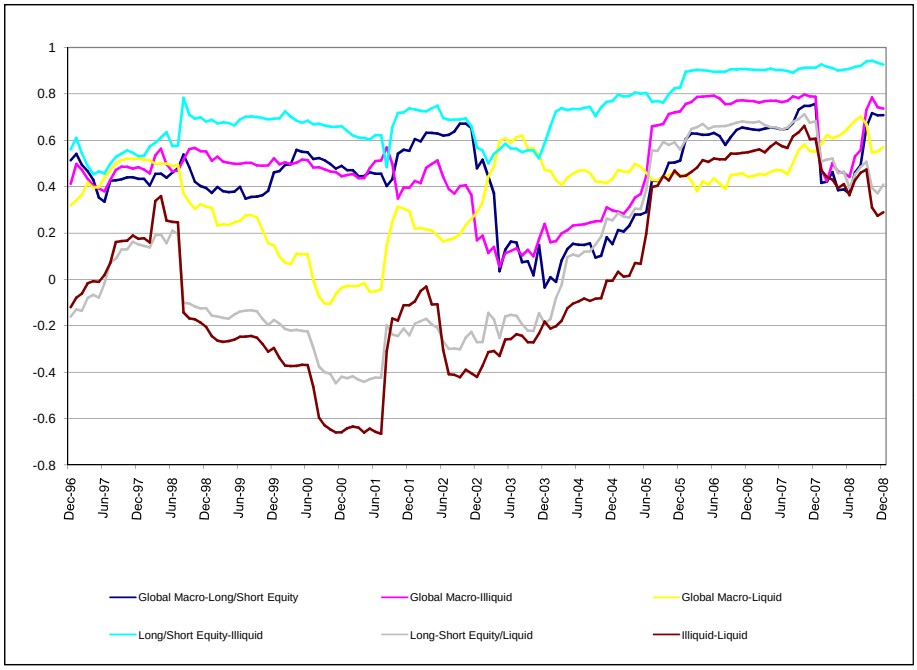


Figure 5: 36-month rolling-window pairwise correlations among monthly returns of four hedge-fund indexes: the CS/Tremont Global Macro index, the CS/Tremont Long-Short index, an index of Illiquid hedge funds (Convertible Bond Arbitrage, Emerging Markets, Event Driven, Fixed Income, and Multi-Strategies), and an index of Liquid hedge funds (Dedicated Shortseller, Equity Market Neutral, and Managed Futures).

this correlation increases over time from 0.60 (1994–2000) to 0.85 (2001–2008), and reached a peak of 0.94 in 2008. This is consistent with Khandani and Lo (2007), who find indirect evidence that liquidity shocks in other parts of the financial system led to hedge-fund managers closing out liquid long/short equity positions to raise cash during the 2007 financial crisis.

	1994 to 2000				2001 to 2008			
	Global Macro	Long/ Short Equity	Illiquid	Liquid	Global Macro	Long/ Short Equity	Illiquid	Liquid
Global Macro	1.00	**0.45**	**0.47**	**0.24**	1.00	**0.56**	**0.67**	**0.48**
Long/Short Equity	**0.45**	1.00	**0.60**	-0.15	**0.56**	1.00	**0.85**	**0.30**
Illiquid	**0.47**	**0.60**	1.00	-0.20	**0.67**	**0.85**	1.00	0.19
Liquid	**0.24**	-0.15	-0.20	1.00	**0.48**	**0.30**	0.19	1.00

Table 2: Correlation coefficients for the monthly returns of four hedge-fund indexes: the CS/Tremont Global Macro index, the CS/Tremont Long-Short index, an index of Illiquid hedge funds (Convertible Bond Arbitrage, Emerging Markets, Event Driven, Fixed Income, and Multi-Strategies), and an index of Liquid hedge funds (Dedicated Shortseller, Equity Market Neutral, and Managed Futures), for two sample periods: January 1994 to December 2000, and January 2001 to December 2008. Correlations significant at the 5% level are shown in bold.

5.2 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 6 and 7.

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 3 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 6 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. The dynamics of PC1 are in line with previous findings on autocorrelation and correlation measures where we find that the systemic risk is increasing starting in 2003.

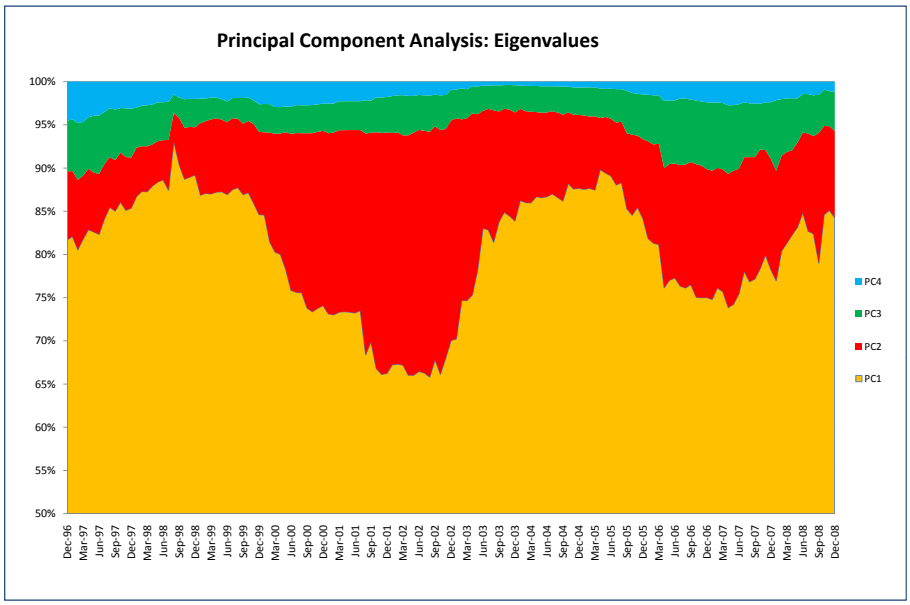


Figure 6: Principal components analysis of the monthly return indexes for Banks, Brokers, Insurers, and Hedge Funds over January 1994 to December 2008. 36-month rolling-window eigenvalues for principal components 1–4 are presented.

Table 3 contains factor loadings for 1994–2000 and 2001–2008 and Figure 7 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

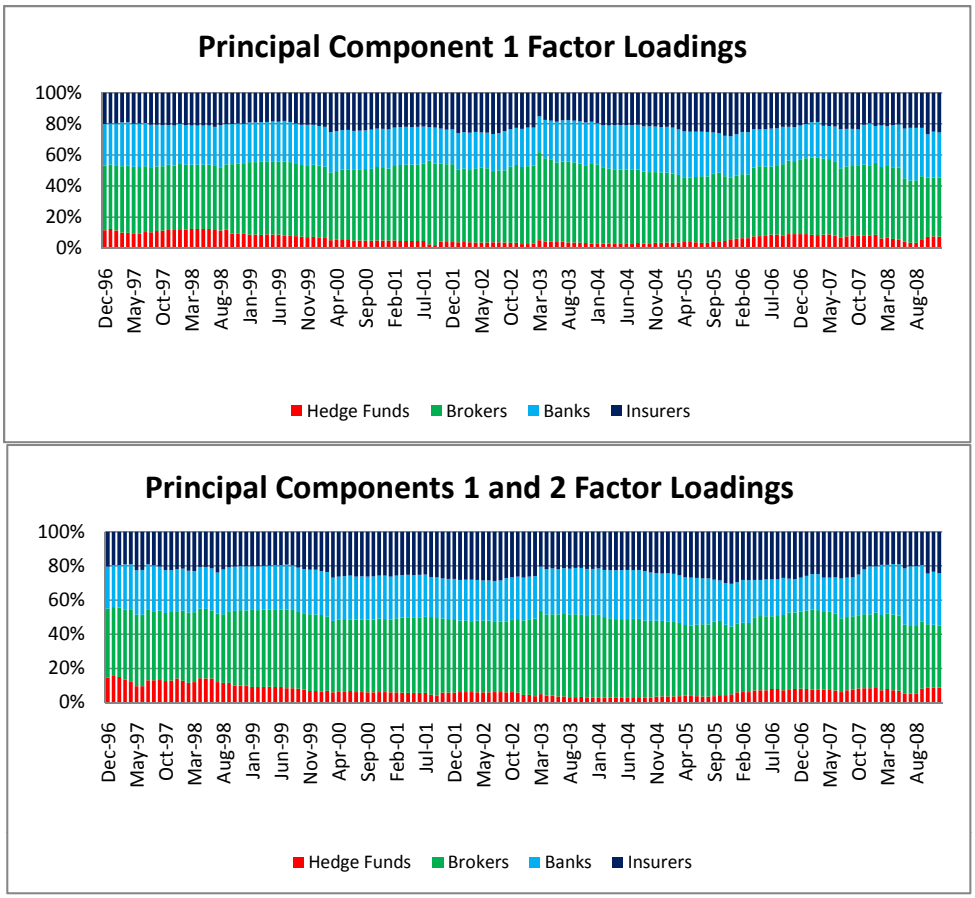


Figure 7: Principal components analysis of the monthly return indexes for Banks, Brokers, Insurers, and Hedge Funds over January 1994 to December 2008. 36-month rolling-window eigenvector exposures for principal component 1 and the sum of principal components 1 and 2 are presented.

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
	1994 to 2000			
Global Macro	0.75	0.58	-0.24	-0.20
Long/Short Equity	0.59	-0.66	0.42	-0.19
Illiquid HFunds	0.29	-0.21	-0.33	0.87
Liquid HFunds	0.03	0.43	0.81	0.40
	2001 to 2008			
Global Macro	0.44	0.39	0.72	-0.37
Long/Short Equity	0.68	-0.30	-0.49	-0.46
Illiquid HFunds	0.54	-0.28	0.21	0.76
Liquid HFunds	0.23	0.83	-0.45	0.26

Table 3: Principal components analysis of the monthly return indexes for financial institutions (Banks, Brokers, Insurers, and Hedge Funds) and four hedge-fund indexes (Global Macro, Long/Short Equity, Illiquid, and Liquid hedge funds) over two time periods: January 1994 to December 2000, and January 2001 to December 2008.

principal component is 0.47 and 0.40 on average, respectively.[15] 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 7 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.[16]

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). These results are consistent with those obtained above in the correlation analysis, and the groupings are plausible given the various business relationships and similarities among these institutions.

We also applied PCA to the four hedge-fund indexes, and find that the first principal component captures 61% (69%) of the variability among the four hedge-fund indexes in 1994–2000 (2001–2008). We show that these hedge-fund indexes are quite different, and each index is uniquely captured by a new principal component. For example, during 1994–2000, Global Macro has an exposure of 0.75 to the first principal component; Long/Short Equity has an exposure of -0.66 to the second component; the Liquid index has a 0.81 exposure to the third component; and the Illiquid index has a 0.87 exposure to the fourth principal component. However, during 2001–2008, the first component captures more variability among these different hedge-fund indexes (69%). This is due to the increased exposure of Long/Short Equity, Illiquid, and Liquid indexes to the first component. These results indicate that hedge funds have become more connected to each other over time, thus increasing

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

[16] We 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.

systemic risk.

5.3 Regime-Switching Models

In Table 4 we report the estimates of the regime-switching model (3) for Hedge Funds, Brokers, Banks, and Insurers, and for the four hedge-fund indexes. For each financial institution index returns are characterized by mean and volatility in each of the two states of the Markov chain Z. Specifically, for each financial institution index, mean and volatility are estimated for both low- and high-volatility states. We follow the convention that $Z=0$ is the low-volatility regime and $Z=1$ is the high-volatility regime. For Brokers, the low-volatility regime is one in which the monthly expected return is 1.94% and the monthly volatility is 5.05%. In comparison, in a high-volatility regime, the mean is 0.40% (but not significant) and the volatility is 10.71%. For Banks, in the low-volatility regime, the mean is positive and significant at 1.70% with 3.78% volatility, and in the high-volatility regime, the mean is -1.53%, and not significantly different from zero, with a volatility of 8.38%. Insurers exhibit similar parameter estimates. Hedge Funds exhibit considerably lower volatility: even in the high-volatility regime, the volatility is only 2.93%, and in the low-volatility regime, it is 1.01%. However, the means are not that different across regimes, presumably because hedge funds are able to both shortsell and use options and other financial instruments that benefit both in high- and low-volatility regimes. Perhaps hedge-fund returns require a three-state regime-switching model. In summary, the volatility in the high-volatility regime is, on average, twice as large as that of the low-volatility regime for financial institutions, and the mean in the low-volatility regime is typically much higher than that of the high-volatility regime, which is often not statistically significant.

In Figure 8, we graph the probability of being in the high-volatility state ($Z=1$) for the whole sample for all four indexes. Hedge Funds have been in a high-volatility state from the beginning of the sample until January 2001. This break is also documented by Bollen and Whaley (2009) and Fung, Hsieh, Naik, and Ramodorai (2008). As discussed in Section 4.1, the early part of the sample was dominated by Global Macro funds and because the volatilities of these funds were typically higher than volatilities of other funds, the early years of the CS/Tremont database exhibit higher volatility than the later years. However, the probability of the high-volatility state for Hedge Funds started to increase after August 2007, spiking in March 2008 which coincided with the demise of Bear Stearns. This probability

Parameter	Hedge Funds		Brokers		Banks		Insurers	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
μ_0	**0.76**	**6.54**	**1.94**	3.32	**1.70**	4.64	**1.15**	3.61
μ_1	**0.70**	**2.38**	0.40	0.34	-1.53	-0.95	-1.70	-0.85
σ_0	**1.01**	**10.72**	**5.05**	10.92	**3.78**	12.24	**3.53**	12.80
σ_1	**2.93**	**13.83**	**10.71**	12.54	**8.38**	8.19	**9.27**	6.20
p_{00}	**0.98**		**0.99**		**0.97**		**0.98**	
p_{11}	**0.99**		**0.97**		**0.90**		**0.87**	
Log Likelihood	-536.75		-786.63		-709.69		-688.92	
Parameter	**Global Macro**		**Long/Short Equity**		**Illiquid Funds**		**Liquid Funds**	
	Estimate	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
μ_0	**1.06**	**9.56**	**0.71**	4.03	**1.11**	11.61	**0.66**	5.47
μ_1	**1.00**	**2.54**	1.07	1.70	-0.81	-1.67	0.14	0.17
σ_0	**0.96**	**11.49**	**1.85**	13.61	**1.02**	12.05	**1.41**	11.99
σ_1	**3.97**	**14.02**	**4.52**	9.37	**2.78**	9.31	**3.42**	4.90
p_{00}	**0.98**		**0.99**		**0.97**		**0.97**	
p_{11}	**0.99**		**0.96**		**0.93**		**0.75**	
Log Likelihood	-565.82		-588.11		-488.97		-514.38	

Table 4: Parameter estimates of a two-state Markov regime-switching model for the return indexes of Banks, Brokers, Insurers, and Hedge Funds, as well as four hedge-fund indexes: Global Macro, Long/Short Equity, an index of Illiquid hedge funds (Convertible Bond Arbitrage, Emerging Markets, Event Driven, Fixed Income, and Multi-Strategies), and an index of Liquid hedge funds (Dedicated Shortseller, Equity Market Neutral, and Managed Futures). P_{00} (P_{11}) is the transition probability of remaining in the low- (high-)volatility state. Parameter estimates that are significant at the 5% level are shown in bold.

declined shortly thereafter, but increased again in July and August 2008. The probability of the high-volatility state for the Hedge funds remained close to 1 thereafter through the end of the sample.

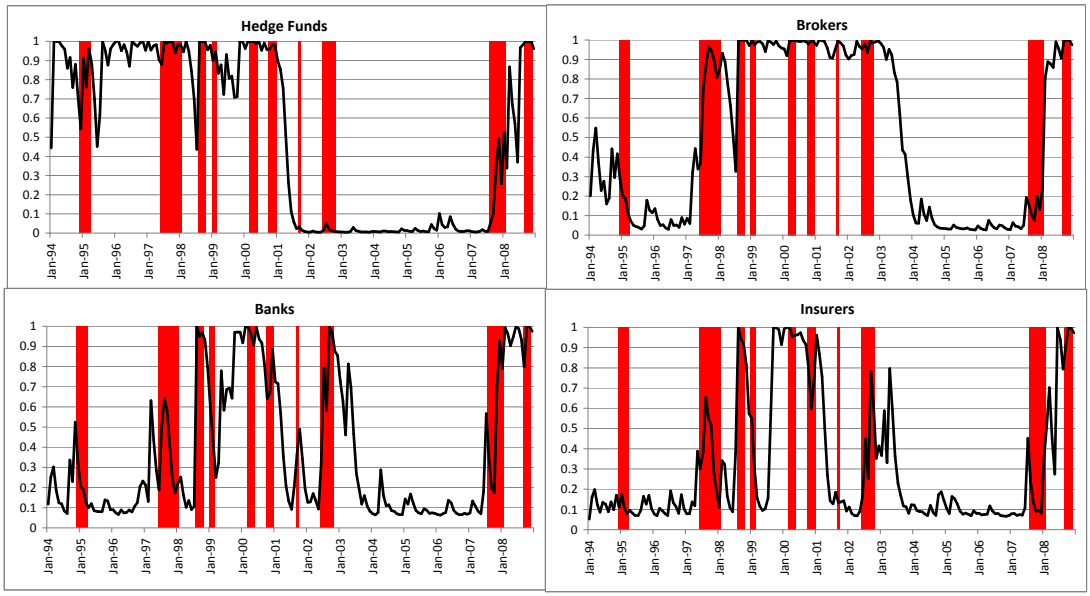


Figure 8: Probabilities of being in the high-volatility state for a two-state Markov regime-switching model for the monthly index returns of Banks, Brokers, Insurers, and Hedge Funds, from January 1994 to December 2008. Red vertical bars represent financial crises.

For Brokers, the time series of the probability of being in the high-volatility state is affected by most of the crisis periods in the sample. In particular, the probability became very high during the 1997–1998 Asian crisis (95%), subsiding after the crisis (the lowest was in July 1998 at 32%), and sharply increasing again in August 1998 during the LTCM crisis. The probability appears to decline just before the crisis (the "calm before the storm"), and then sharply increases. The probability stayed high (around 100%) until May 2003, then decreased and stayed low (less than 5%) until August 2007, the start of the Subprime Mortgage Crisis of 2007 (15%). However, the largest increase was in March 2008 with the default of Bear Stearns.

Not surprisingly, the high-volatility states of the Bank index are also associated with crisis periods. During the Asian financial crisis, the probability of the high-volatility state for Banks increased to 64% in August 1997, decreasing shortly thereafter, and then increasing quickly during the LTCM crisis (almost 100% probability). Additional spikes occurred during

the Internet crash of March 2000, the Enron bankruptcy, and throughout the recent financial crisis, starting in July 2007 and later in November 2007 when most banks (e.g., HSBC, Citigroup, Credit Suisse, Bank of America, and SunTrust Banks) incorporated structured investment vehicles (SIVs) onto their balance sheets (Gorton, 2008). The large increase in the probability of the high-volatility state may be related to the SIVs through two channels: direct channel (since several banks also maintained brokerage units) and indirect channel (since the most troubled banks were counterparties of most major brokerage firms).

For Insurers, the probability of the high-volatility state stayed low until the Asian crisis of August 1997 (66%). Then it went down and spiked during the LTCM crisis (almost 100%). After this it went down to 10% and increased again in October, 1999 (almost 100%), possibly related to Y2K-related business. It went down in February 2001 and increased again during the Enron crisis, recovering after April 2003. Since then, the probability was about 10% and similar to Banks; it increased to 45% in July 2007, right before the sub-prime mortgage crisis. Then the probability of the high-volatility state briefly recovered and increased again in March 2008. It decreased in May 2008, but in June 2008, just before the Global Financial Crisis of 2008, it increased again and remained high until the end of the sample, similar to other financial institutions.

While each time series of probabilities may indicate some kind of distress for the corresponding sector, a natural measure of systemic risk is when all four indexes are simultaneously in their high-volatility state. This commonality in the behavior of financial institutions can be captured by the joint probability of the high-volatility state, for which a conservative estimate (assuming that high-volatility states are positively correlated among the four indexes) is the product (4) of the four state-probabilities (see footnote 9). This estimate of the joint probability of the high-volatility regime is plotted in Figure 9. For most of the sample, this joint probability is close to zero. However, it approached 100% during the LTCM crisis (August 1998), the Internet crash (March 2000), and the recent Global Financial Crisis of 2008 (September to October 2008). Interestingly, the probability during the sub-prime mortgage crisis is very small, as different financial institutions did not move in tandem and were affected differently by these events.

To check the independence among the high-volatility states of the four indexes, we compute the unconditional probability $A_{p,t}$ of this event using (5), which yields an estimate of 0.51%, i.e. out of the 180 months in our sample, we should expect to see this event in 0.92

months. In fact, we find that for 16 months, i.e., 17 times more frequently than expected, all four indexes were in the high-volatility regime. Therefore, our result is almost certainly not due to chance, but due to some commonality in the high-volatility regimes for these financial institutions.

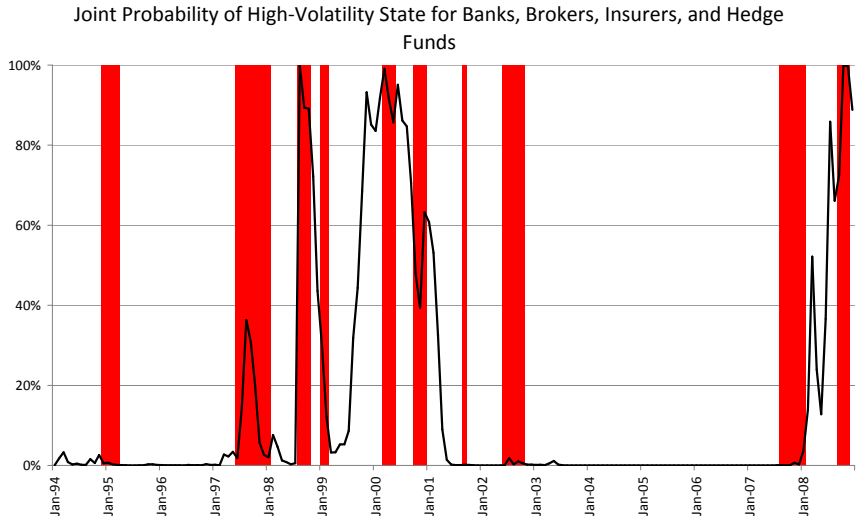


Figure 9: The joint probability of being in the high-volatility state for the monthly return indexes of Banks, Brokers, Insurers, and Hedge Funds from January 1994 to December 2008. Red vertical bars represent financial crises.

An alternative measure of systemic risk is constructed by averaging the four probabilities of being in the high-volatility state as in (7). This aggregate systemic risk measure is plotted in Figure 10. The average probability is relatively low in the first part of the sample (30%) and is mostly driven by Hedge Funds. During the Asian crisis, the role of Brokers greatly increased, leading to the increase in the average probability to 77% in August 1997. During the LTCM crisis, the average probability increased to 100%, with all four indexes contributing equally. After the crisis, the role of Hedge Funds and Brokers remained the same, while the contribution of Banks and Insurance companies to the average probability greatly decreased. The probability started to increase after July 1999, mainly due to Insurers, and spiked to almost a 100% in March 2000 (the Internet crash), then decreased only increasing to 70% during the Enron crisis.

Before January 2001, all four indexes were equal contributors to the average probability, but starting in 2001, the contribution of Hedge Funds decreased to almost 0%, possibly due to the decreasing role of Global Macro hedge funds in the CS/Tremont database (see the

discussion in Section 4.3), and the fact that as a group, hedge funds tend to recover more quickly from market dislocation (often through attrition, which gives rise to new funds). Since January 2001, Banks and Brokers were the biggest contributors to this average probability, with virtually no impact from Hedge Funds until September 2007. During this time period hedge funds were in a low-volatility state, were mostly not affected by the WorldCom and Enron crises, and experienced the growth in assets under management. The average probability began increasing in July 2007, mostly driven by Banks and Insurance companies, then declined in October 2007, only to increase again in November 2007 with Hedge Funds and Banks being the biggest contributors. By March 2008, in the face of the Bear Stearns debacle, all four indexes contributed equally to the sharply rising average probability, and by the end of our sample, the average probability of the high-volatility state reached 100%.

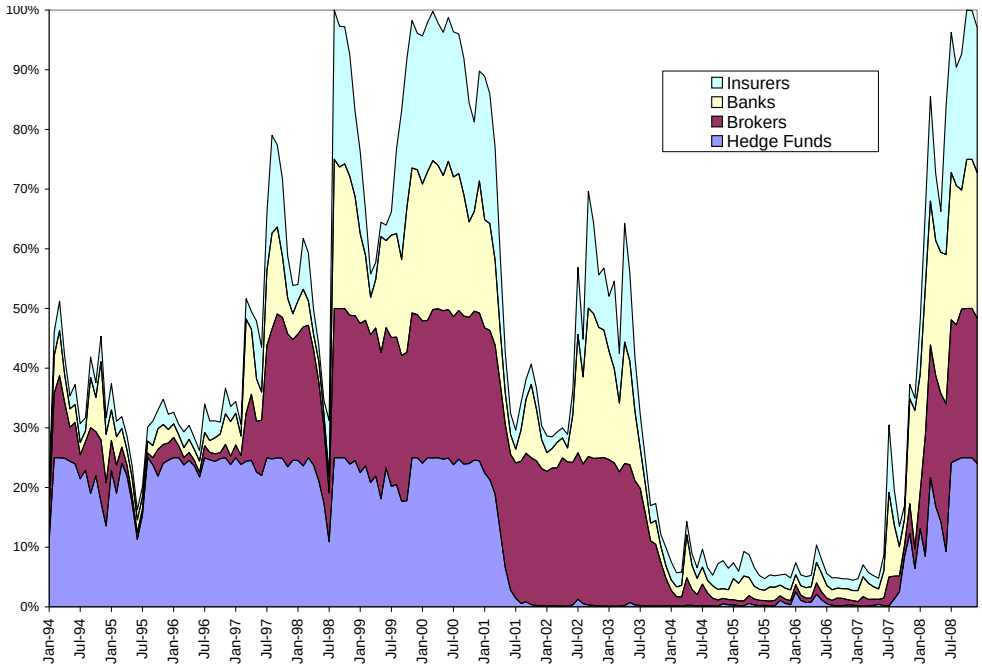


Figure 10: The average probabilities of being in the high-volatility state for monthly return indexes of Banks, Brokers, Insurers, and Hedge Funds from January 1994 to December 2008.

For completeness, in Table 4 we report the parameter estimates of the regime-switching model for the four hedge-fund indexes: Global Macro, Long/Short Equity, Illiquid, and Liquid indexes. Volatility in the high-volatility state is usually twice volatility in the low-volatility state for each of the indexes. The monthly mean returns for the Illiquid and Liquid indexes are higher in the low-volatility state than in the high-volatility state. However, for

Global Macro, the mean returns are about the same in both states (1.06% when $Z=0$, and 1.00% when $Z=1$). For Long/Short Equity, the mean return is 0.71% when $Z=0$, and 1.07% when $Z=1$, which is consistent with the intuition that Long/Short Equity managers are long volatility. We provide a more detailed discussion of the time series properties of the high-volatility-state probabilities for these sub-sector indexes in the Appendix.

In conclusion, both systemic risk measures show instances when systemic risk is on the rise and which financial institutions contribute the most to these increases.

5.4 Granger Causality Tests

In Table 5 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 samples are depicted in Figure 11. Relationships that are significant at the 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.

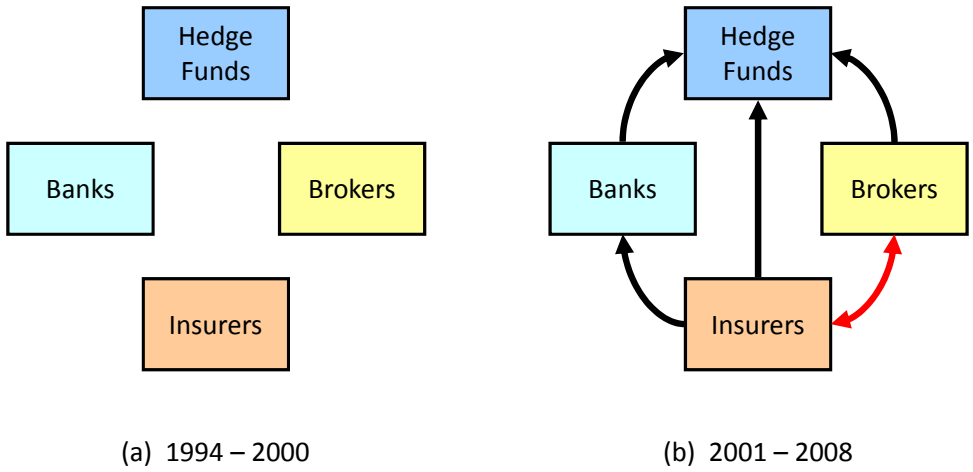


Figure 11: Linear Granger-causality relationships (at the 5% level of statistical significance) among the monthly returns of Banks, Brokers, Insurers, and Hedge Funds over two samples: (a) January 1994 to December 2000, and (b) January 2001 to December 2008. All p-values are adjusted for autocorrelation and heteroskedasticity.

We do not observe any significant causal relationships between Banks, Brokers, Insurers,

	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 5: 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 the 5% level are shown in bold, and p-values are adjusted for autocorrelation and heteroskedasticity.

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 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 5.5.

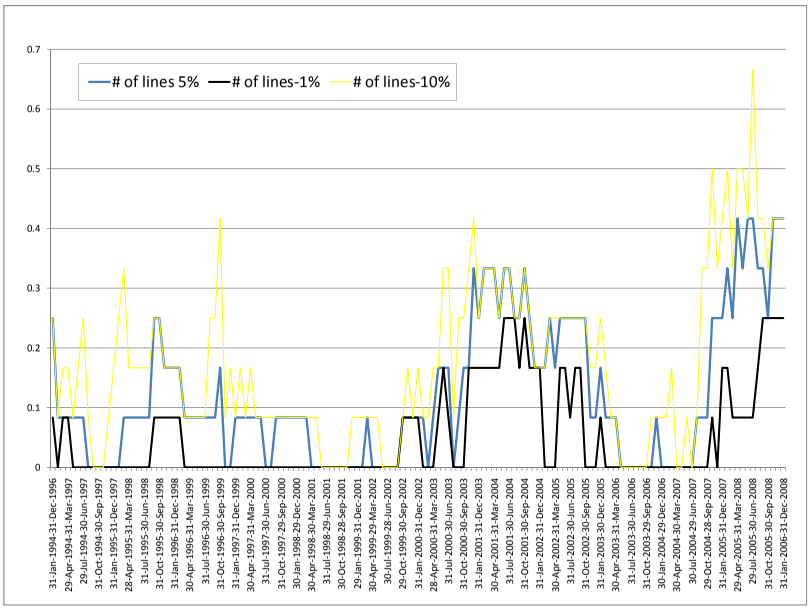
We also investigate dynamic causality among the return indexes of Banks, Brokers, Insurers, and Hedge Funds using a 36-month rolling window. The results are presented in Figure 12. Specifically, we calculate the proportion of significant causal relationships at 1%, 5%, and 10% significance levels out 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 processing 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 12 also depicts the presence of Granger causality to Hedge Funds over time at the 5% level of significance. Consistent with results found in Table 5 and depicted in Figure 11, 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.

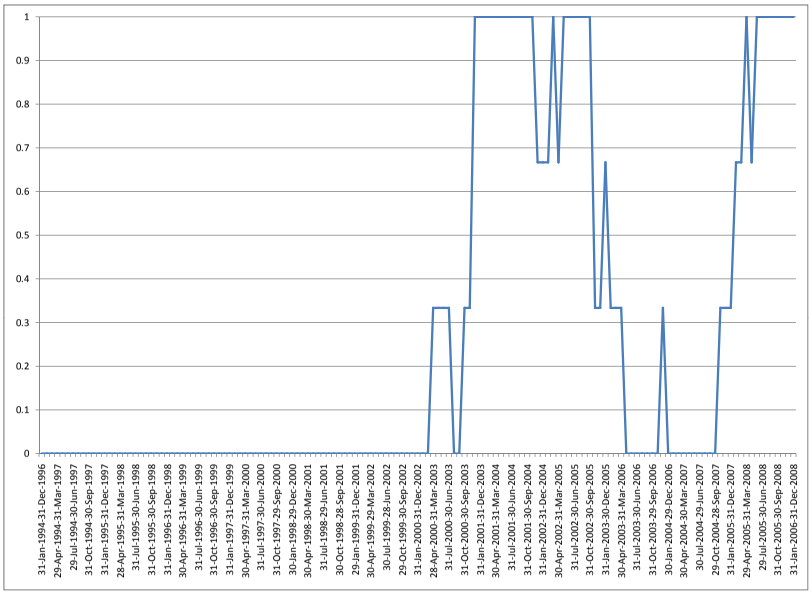
These results are also surprising since we are using heteroskedasticity- and autocorrelation-adjusted test statistics for the monthly returns of aggregate indexes. In a framework where all markets clear and past information is reflected in current prices, returns should not exhibit any systemic time-series 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 5 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 13. For the 1994–2000 sample, the results in Figure 13 are similar to those in Figure 11 where we do not find any causality among Brokers, Banks, Hedge Funds, and Insurers. In the second part of the sample (2001–2008), we find that after adjusting for the S&P 500, shocks to Banks propagate to Hedge Funds and the Insurers affect Brokers; however, shocks to other financial institutions do not affect Banks and Insurers. In this respect, Banks and Insurers



(a)



(b)

Figure 12: 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.

appear to be the most contagious of the four types of financial institutions.[17]

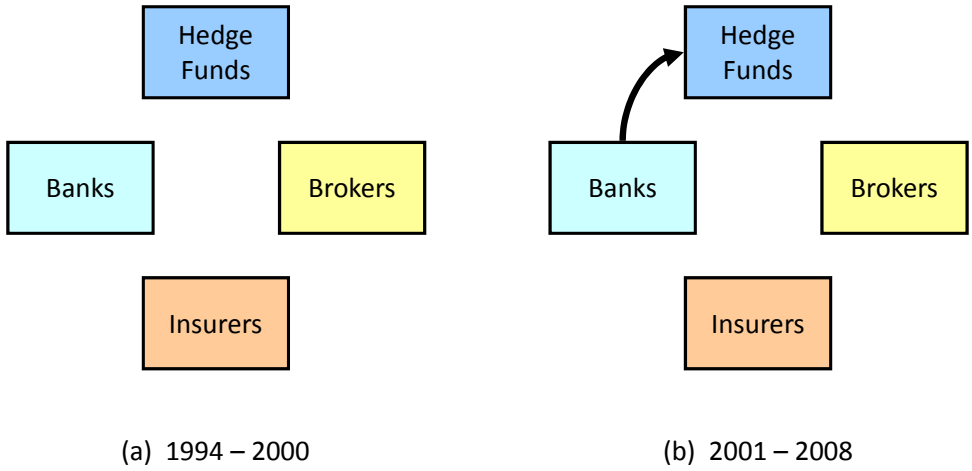


Figure 13: Linear Granger-causality relationships (at the 5% level of statistical significance) among the residual returns (from a market-model regression against the S&P 500) of Banks, Brokers, Insurers, and Hedge Funds over two samples: (a) January 1994 to December 2000, and (b) January 2001 to December 2008. All p-values are adjusted for autocorrelation and heteroskedasticity.

Nevertheless, our analysis is based on aggregate indexes, and all financial institutions may not exhibit these patterns. Therefore, we produce more disaggregated results by separating the hedge fund index into four corresponding hedge-fund sub-indexes: Global Macro, Long/Short Equity, Illiquid and Liquid hedge funds. The construction of these sub-indexes is described in Section 4.1, and regime-switching estimates and Granger-causality tests are provided in the Appendix.

Table 6 presents p-values of nonlinear Granger causality likelihood ratio tests (see Section 3.4) for the monthly residual returns indexes of Banks, Brokers, Insurers, and the four hedge-fund indexes over the two samples: 1994–2000 and 2001–2008. This analysis shows that causal relationships are even stronger if we take into account both the level of the mean and the level of risk that these financial institutions may face, i.e., their volatilities. The presence of strong nonlinear Granger-causality relationships is detected in both samples. Moreover, in the 2001–2008 sample, we find that almost all financial institutions were affected by the past level of risk of other financial institutions.[18]

[17]The p-value for the Granger-causal link from Insurers to Brokers is 6.3%.

[18]We consider only pairwise causalities due to significant multicollinearity among the returns.

	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers
	1994 to 2000							2001 to 2008						
Global Macro		**2.5**	**0.8**	6.8	**0.0**	49.5	14.3		**0.0**	**0.0**	53.6	**0.9**	**0.0**	83.8
Long/Short Equity	51.6		**0.0**	21.8	**4.1**	**0.0**	**2.5**	**0.0**		**0.0**	**0.0**	**1.8**	**0.0**	**1.8**
Illiquid Hfunds	64.1	**0.1**		**0.0**	**0.0**	**0.1**	**0.0**	**0.0**	**0.0**		54.7	**1.8**	**1.8**	**0.0**
Liquid Hfunds	94.9	**0.1**	**0.0**		**0.0**	**0.5**	**0.6**	**1.2**	**0.0**	**0.0**		**0.0**	**0.0**	**0.0**
Brokers	**0.6**	**0.0**	**0.0**	35.6		23.7	74.9	**0.0**	5.8	**0.6**	15.6		**0.0**	94.2
Banks	98.7	**0.0**	**0.0**	51.5	**0.0**		78.1	**0.0**	**4.1**	**0.0**	36.7	**0.7**		**0.0**
Insurers	96.7	7.7	**0.1**	70.0	82.0	93.1		**0.0**	72.7	**0.0**	**0.0**	**0.2**	**0.0**	

Table 6: p-values of nonlinear Granger-causality likelihood ratio tests for the monthly residual returns indexes of Banks, Brokers, Insurers, and the four hedge-fund indexes (Global Macro, Long/Short Equity, Illiquid and Liquid indexes), for two sub-samples: January 1994 to December 2000, and January 2001 to December 2008. Statistics that are significant at the 5% level are shown in bold. All p-values are adjusted for autocorrelation and heteroskedasticity.

Note that linear Granger-causality tests provide causality relationships based only on the means, whereas nonlinear Granger-causality tests also take into account the linkages among 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.

5.5 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.[19]

[19]Given 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 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 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 the 5% level are depicted, and to conserve space, we show results only for five of the 145 sub-periods in Figures 14–18: 1994–1996, 1996–1998, 1999–2001, 2002–2004, and 2006–2008.[20] For each sub-period, we also provide summary statistics for the monthly returns of 100 largest (with respect to AUM) financial institutions in Table 7, including the asset-weighted autocorrelation, correlation,[21] standard deviation,[22] the normalized number of connections, [23] and the total number of connections.

We find that Granger-causality relationships are highly dynamic among these financial institutions. Results are presented in Table 7 and Figures 14–18. 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

the robustness of the results. Results are provided upon request.

[20]The complete set of graphs is available upon request. Also, to 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`.

[21]An asset-weighted correlation ρ is simply:

$$\rho \quad = \quad \frac{\sum_{i=1,j=2,i\neq j}^{i=n,j=n} \omega_i \omega_j \rho_{i,j}}{\sum_{i=1,j=2,i\neq j}^{i=n,j=n} \omega_i \omega_j}$$

where $\omega_i = \frac{A_i}{\sum_{i=1}^{n} A_i}$, A_i is the average AUM (assets under management) for a financial institution i during the time period considered, and n is the total number of financial institutions.

[22]An asset-weighted standard deviation σ is simply the usual standard deviation of a portfolio:

$$\sigma \quad = \quad \sqrt{\boldsymbol{\omega}' \boldsymbol{\Sigma} \boldsymbol{\omega}}$$

where $\boldsymbol{\omega}$ is a column-vector of financial institution asset weights, and $\boldsymbol{\Sigma}$ is the covariance matrix of all financial institutions.

[23]The normalized number of connections is the fraction of all significant (at the 5% level) connections between financial institutions out of the total possible connections. n financial institutions have $n(n-1)$ total possible connections.

Sector	Asset Weighted AutoCorr	Asset Weighted Corr	Asset Weighted σ	# 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	0.30	0.04	6%				583			
Hedge Funds	0.03	0.31	0.03	7%	3%	6%	6%	41	21	36	37
Brokers	-0.15	0.54	0.06	3%	5%	6%	4%	18	29	36	24
Banks	-0.03	0.38	0.04	6%	7%	9%	7%	40	46	54	44
Insurers	-0.10	0.25	0.04	5%	6%	6%	9%	33	38	35	51
January 1996 to December 1998											
All	-0.03	0.43	0.06	9%				856			
Hedge Funds	0.08	0.36	0.04	14%	6%	5%	3%	82	38	30	20
Brokers	-0.04	0.54	0.10	13%	9%	9%	9%	81	53	54	57
Banks	-0.09	0.54	0.06	11%	8%	11%	10%	71	52	65	64
Insurers	0.02	0.40	0.05	9%	9%	7%	6%	57	54	44	34
January 1999 to December 2001											
All	-0.09	0.35	0.06	5%				520			
Hedge Funds	0.17	0.18	0.02	5%	5%	5%	9%	32	32	33	58
Brokers	0.03	0.63	0.12	8%	9%	3%	5%	53	52	19	29
Banks	-0.09	0.48	0.07	5%	3%	4%	7%	30	17	25	42
Insurers	-0.20	0.53	0.08	5%	3%	2%	6%	32	16	14	36
January 2002 to December 2004											
All	-0.08	0.38	0.04	6%				611			
Hedge Funds	0.20	0.15	0.01	10%	3%	9%	5%	61	20	56	29
Brokers	-0.09	0.66	0.07	8%	4%	4%	6%	53	23	26	39
Banks	-0.14	0.49	0.04	9%	3%	4%	5%	55	16	24	30
Insurers	0.00	0.32	0.04	8%	6%	9%	6%	48	40	55	36
January 2006 to December 2008											
All	0.08	0.36	0.06	13%				1244			
Hedge Funds	0.23	0.33	0.02	10%	13%	5%	13%	57	82	31	83
Brokers	0.23	0.54	0.08	12%	17%	9%	12%	78	102	55	73
Banks	0.02	0.46	0.07	23%	12%	10%	9%	142	74	58	54
Insurers	0.12	0.37	0.07	13%	16%	12%	16%	84	102	73	96

Table 7: Summary statistics of linear Granger-causality relationships (at the 5% level of statistical significance) among the monthly returns of the largest (as determined by average AUM for hedge funds and average market capitalization for brokers, insurers, and banks during the time period considered) 25 banks, brokers, insurers, and hedge funds 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, correlations, standard deviations, 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. All p-values are adjusted for autocorrelation and heteroskedasticity.

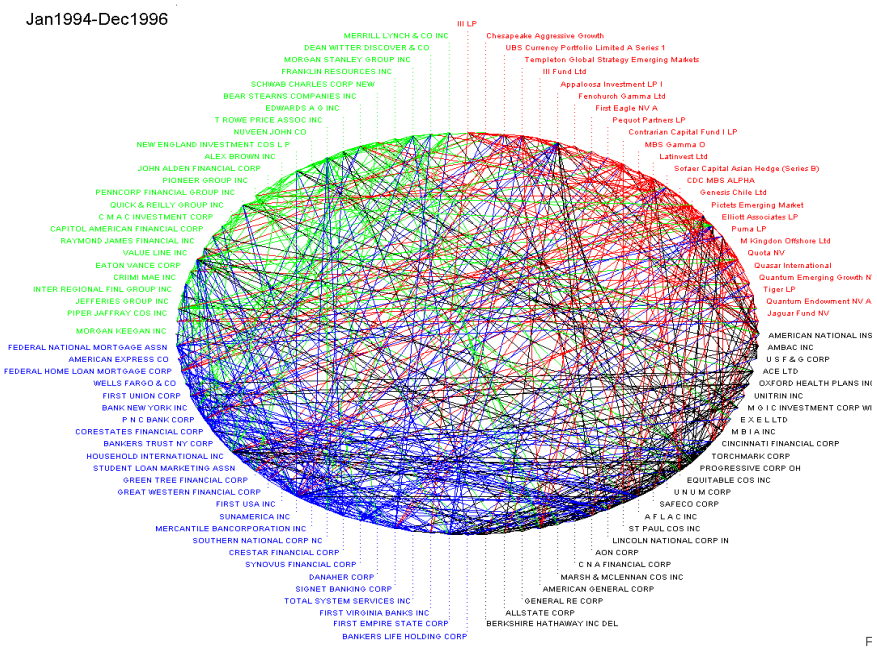


Figure 14: Network Diagram of Linear Granger-causality relationships that are statistically significant at the 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 1994 to December 1996. The type of institution causing the 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.

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 connections) in 2006–2008, which was right before and during the recent Financial Crisis of 2007–2009 according to Table 7. Both LTCM 1998 crisis and the recent Financial Crisis of 2007–2009 were associated with liquidity and credit problems, and the increase in interconnections between financial institutions was a significant systemic risk measure, especially for the recent Financial Crisis of 2007–2009 which experienced the highest interconnection during the whole time-period. In contrast, right before and during the Internet Crash of 2000 (2002–2004), there were only 520 connections between financial institutions (5% of the total possible connections).

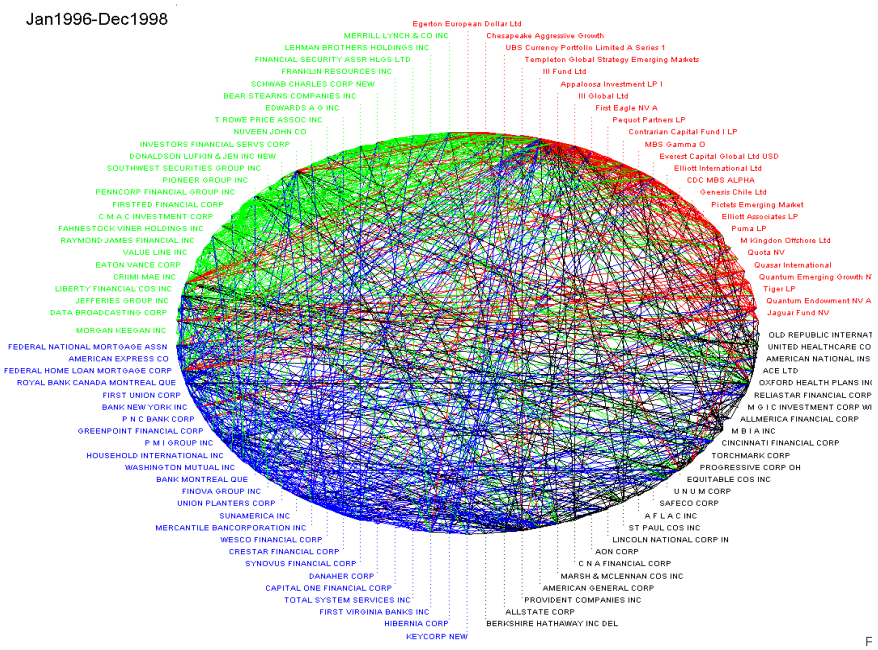


Figure 15: Network diagram of linear Granger-causality relationships that are statistically significant at the 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 1996 to December 1998. The type of institution causing the 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 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.

Table 7 shows that asset-weighted autocorrelations for the overall financial system were negative for all samples; however, in 2006–2008, the period that includes the Subprime Mortgage Crisis of 2007 and the Global Financial Crisis of 2008, the autocorrelations became positive. When we separate the asset-weighted autocorrelation into institutional components, we find that during all periods, hedge-fund asset-weighted autocorrelations were positive, but were mostly negative for all other financial institutions.[24] However, in the last sample period (2006–2008), the asset-weighted autocorrelations became positive for all financial institutions. As a result, the recent Financial Crisis of 2007–2009 experienced the most illiquidity and connectivity among financial institutions.[25] In summary, we find that all four financial and insurance companies have become highly interrelated and generally less liquid over the past decade, increasing the level of systemic risk in the finance and insurance industries.

To separate contagion and common-factor exposure, we regress each company's monthly

[24]starting 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.

[25]Asset-weighted correlations vary, peaking during the LTCM 1998 crisis (0.43). Asset-weighted monthly standard deviations have been relatively stable, ranging between 4% and 6%.

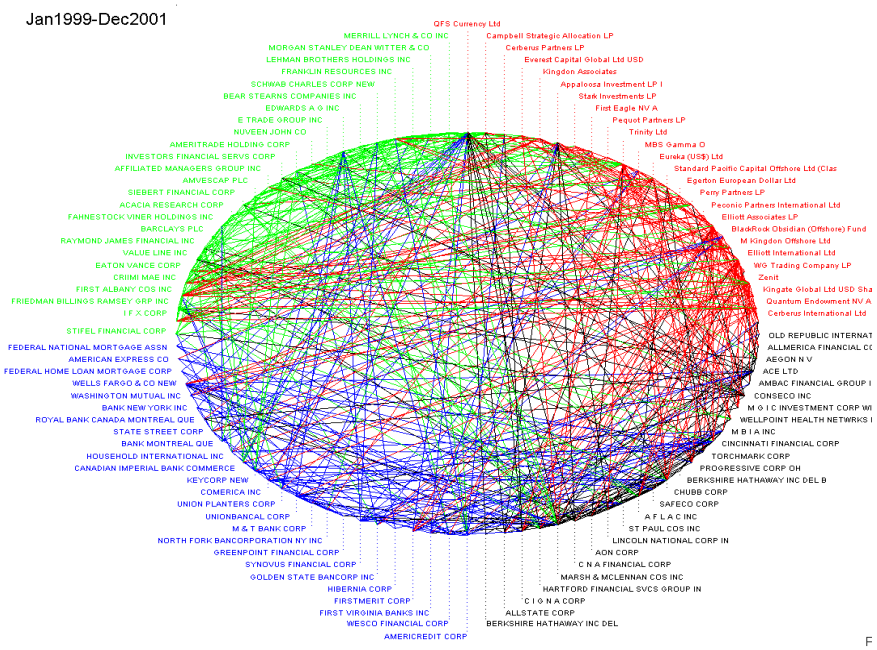


Figure 16: Network diagram of linear Granger-causality relationships that are statistically significant at the 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 1999 to December 2001. The type of institution causing the 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.

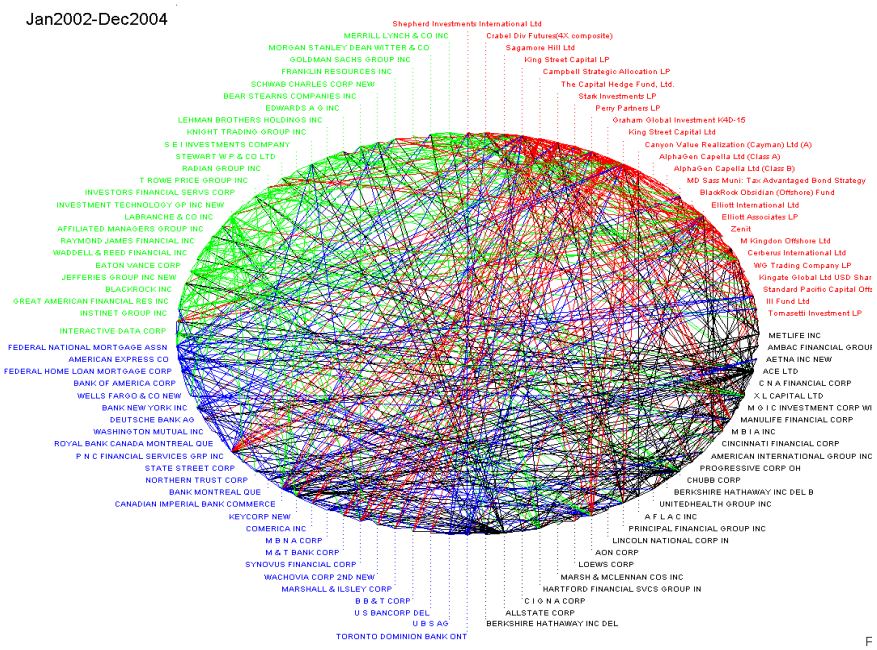


Figure 17: Network diagram of linear Granger-causality relationships that are statistically significant at the 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 2002 to December 2004. The type of institution causing the 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.

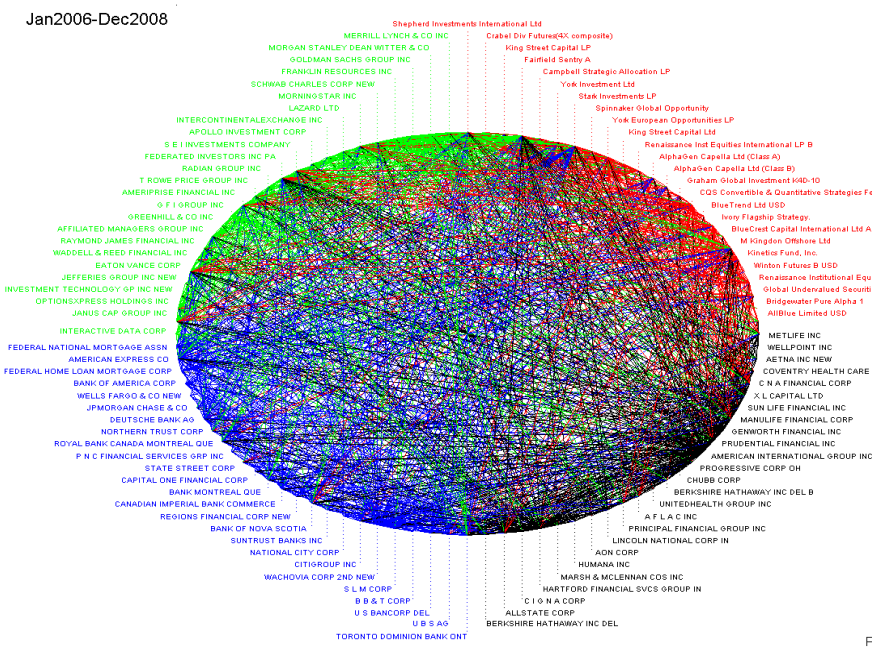


Figure 18: Network diagram of linear Granger-causality relationships that are statistically significant at the 5% level among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 2006 to December 2008. The type of institution causing the 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.

returns on the S&P 500 and re-run the linear Granger causality tests on the residuals. We 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.[26]

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

The ultimate purpose of any systemic risk measure is to provide an actionable early warning signal, and in this section, we construct an array of such indicators based on Granger-causality networks of Section 5.5 and apply it to specific financial institutions affected by the Financial Crisis of 2007–2009. We build upon Section 5.5 and consider October 2002–September 2005 as the sample on 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, which is consistent with the approach in Acharya et al. (2010). The October 2002–September 2005 period is chosen because this is the first 36-month rolling sub-period in which the number of connections increased (reaching 701, which represents 7% of the total possible connections) and the overall system and individual financial-institution autocorrelations became and stayed positive before the Financial Crisis of 2007–2009. For each financial institution, we compute the following set of systemic risk measures:

- **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.
- **Number of "Out-to-Other" Connections**: The number of other types of financial institutions that are significantly Granger-caused by this financial institution.

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

- **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.[27]

As in Section 5.5, 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. The top 20 ranked financial institutions with respect to each of the network-based measures listed above are reported in Table 8.

To evaluate the predictive power of these rankings, we first compute the maximum financial losses (both in dollar and percentage terms) suffered by each of the 100 institutions during the crisis period from July 2007 to December 2008. The maximum dollar loss (MaxLoss) for a financial institution is 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. The maximum percentage loss (Max%Loss) for a financial institution is the MaxLoss divided by the market capitalization or fund size of the institution at the end of June 2007. We then rank all financial institutions from 1 to 100 for both MaxLoss and Max%Loss. We then estimate univariate regressions for each of the two loss rankings on the institutions' systemic-risk rankings from Table 8. The results are reported in Table 9. For each regression, we report the β coefficient, the t-statistic, p-value, and the Kendall (1938) τ rank-correlation coefficient.

[27]Specifically, 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.

In	
PRINCIPAL FINANCIAL GROUP INC	45
BERKSHIRE HATHAWAY INC DEL	28
INSTINET GROUP INC	24
Cerberus International Ltd	21
BERKSHIRE HATHAWAY INC DEL B	21
M Kingdon Offshore Ltd	19
Perry Partners LP	17
LABRANCHE & CO INC	17
KEYCORP NEW	15
Sagamore Hill Ltd	14
EDWARDS A G INC	14
JEFFERIES GROUP INC NEW	13
WADDELL & REED FINANCIAL INC	13
BANK MONTREAL QUE	13
AMERITRADE HOLDING CORP NEW	12
INVESTORS FINANCIAL SERVS CORP	12
STEWART W P & CO LTD	12
TORONTO DOMINION BANK ONT	12
MANULIFE FINANCIAL CORP	11
Elliott International Ltd	10

Out	
WELLS FARGO & CO NEW	26
PROGRESSIVE CORP OH	24
BANK OF AMERICA CORP	20
CITIGROUP INC	19
STEWART W P & CO LTD	18
FEDERAL NATIONAL MORTGAGE ASSN	17
U B S AG	16
UNITEDHEALTH GROUP INC	16
INVESTMENT TECHNOLOGY GP INC NEW	15
LEHMAN BROTHERS HOLDINGS INC	14
T ROWE PRICE GROUP INC	14
EATON VANCE CORP	14
AMERICAN EXPRESS CO	14
M B I A INC	14
JEFFERIES GROUP INC NEW	13
M B N A CORP	13
Graham Global Investment K4D-15	12
RAYMOND JAMES FINANCIAL INC	12
WACHOVIA CORP 2ND NEW	12
AMBAC FINANCIAL GROUP INC	12

In+Out	
PRINCIPAL FINANCIAL GROUP INC	51
STEWART W P & CO LTD	30
INSTINET GROUP INC	29
BERKSHIRE HATHAWAY INC DEL	29
WELLS FARGO & CO NEW	28
PROGRESSIVE CORP OH	27
JEFFERIES GROUP INC NEW	26
BERKSHIRE HATHAWAY INC DEL B	26
U B S AG	25
Cerberus International Ltd	23
M Kingdon Offshore Ltd	23
T ROWE PRICE GROUP INC	23
LABRANCHE & CO INC	22
M B N A CORP	21
Graham Global Investment K4D-10	20
AMERITRADE HOLDING CORP NEW	20
EATON VANCE CORP	20
CITIGROUP INC	20
BANK OF AMERICA CORP	20
TORONTO DOMINION BANK ONT	20

In from Other	
PRINCIPAL FINANCIAL GROUP INC	41
BERKSHIRE HATHAWAY INC DEL	25
INSTINET GROUP INC	20
BERKSHIRE HATHAWAY INC DEL B	20
M Kingdon Offshore Ltd	18
Cerberus International Ltd	17
LABRANCHE & CO INC	16
Perry Partners LP	13
WADDELL & REED FINANCIAL INC	13
KEYCORP NEW	13
EDWARDS A G INC	12
STEWART W P & CO LTD	12
BANK MONTREAL QUE	12
AMERITRADE HOLDING CORP NEW	11
INVESTORS FINANCIAL SERVS CORP	11
JEFFERIES GROUP INC NEW	11
Sagamore Hill Ltd	10
TORONTO DOMINION BANK ONT	10
MANULIFE FINANCIAL CORP	10
Elliott International Ltd	9

Out to Other	
WELLS FARGO & CO NEW	23
PROGRESSIVE CORP OH	20
BANK OF AMERICA CORP	17
STEWART W P & CO LTD	16
UNITEDHEALTH GROUP INC	15
INVESTMENT TECHNOLOGY GP INC NEW	14
CITIGROUP INC	14
U B S AG	14
FEDERAL NATIONAL MORTGAGE ASSN	12
AMERICAN EXPRESS CO	12
AMBAC FINANCIAL GROUP INC	12
Kingate Global Ltd USD Shares	11
T ROWE PRICE GROUP INC	11
JEFFERIES GROUP INC NEW	11
X L CAPITAL LTD	11
M B N A CORP	10
M B I A INC	10
Graham Global Investment K4D-10	9
AMERICAN INTERNATIONAL GROUP INC	9
ACE LTD	9

In+Out Other	
PRINCIPAL FINANCIAL GROUP INC	45
STEWART W P & CO LTD	28
BERKSHIRE HATHAWAY INC DEL	26
WELLS FARGO & CO NEW	25
INSTINET GROUP INC	23
U B S AG	23
BERKSHIRE HATHAWAY INC DEL B	23
M Kingdon Offshore Ltd	22
JEFFERIES GROUP INC NEW	22
PROGRESSIVE CORP OH	22
LABRANCHE & CO INC	20
T ROWE PRICE GROUP INC	19
Cerberus International Ltd	18
INVESTMENT TECHNOLOGY GP INC NEW	18
BANK OF AMERICA CORP	17
KEYCORP NEW	17
EDWARDS A G INC	16
UNITEDHEALTH GROUP INC	16
X L CAPITAL LTD	16
Graham Global Investment K4D-10	15

Closeness	
WELLS FARGO & CO NEW	1.74
PROGRESSIVE CORP OH	1.76
BANK OF AMERICA CORP	1.80
CITIGROUP INC	1.81
STEWART W P & CO LTD	1.82
FEDERAL NATIONAL MORTGAGE ASSN	1.83
U B S AG	1.84
UNITEDHEALTH GROUP INC	1.84
INVESTMENT TECHNOLOGY GP INC NEW	1.85
LEHMAN BROTHERS HOLDINGS INC	1.86
T ROWE PRICE GROUP INC	1.86
EATON VANCE CORP	1.86
AMERICAN EXPRESS CO	1.86
M B I A INC	1.86
JEFFERIES GROUP INC NEW	1.87
M B N A CORP	1.87
Graham Global Investment K4D-15	1.88
RAYMOND JAMES FINANCIAL INC	1.88
WACHOVIA CORP 2ND NEW	1.88
AMBAC FINANCIAL GROUP INC	1.88

Eigenvector Centrality	
PROGRESSIVE CORP OH	0.31
WELLS FARGO & CO NEW	0.31
BANK OF AMERICA CORP	0.24
CITIGROUP INC	0.22
STEWART W P & CO LTD	0.21
UNITEDHEALTH GROUP INC	0.19
FEDERAL NATIONAL MORTGAGE ASSN	0.19
INVESTMENT TECHNOLOGY GP INC NEW	0.18
AMBAC FINANCIAL GROUP INC	0.16
M B N A CORP	0.16
T ROWE PRICE GROUP INC	0.15
X L CAPITAL LTD	0.15
U B S AG	0.14
Kingate Global Ltd USD Shares	0.14
AMERICAN EXPRESS CO	0.14
BlackRock Obsidian (Offshore) Fund	0.14
LEHMAN BROTHERS HOLDINGS INC	0.14
Crabel Div Futures(4X composite)	0.13
WASHINGTON MUTUAL INC	0.13
M B I A INC	0.12

Table 8: Granger-causality-network-based measures of systemic risk for a sample of 100 financial institutions consisting of the 25 largest (as determined by average AUM for hedge funds and average market capitalization for brokers, insurers, and banks during the time period considered) banks, brokers, insurers, and hedge funds for the sample period from October 2002 to September 2005. Only the 20 highest-scoring institutions in each category are displayed, and all connections are based on Granger-causal statistics at the 5% level of statistical significance.

Measure	MaxLoss				Max%Loss			
	Coeff	t-stat	p-value	Kendall τ	Coeff	t-stat	p-value	Kendall τ
In Connections	-0.08	-0.75	0.46	-0.06	0.03	0.25	0.80	0.02
Out Connections	0.19	1.79	0.08	0.13	**0.23**	**2.23**	**0.03**	**0.16**
In+Out Connections	0.12	1.16	0.25	0.09	0.16	1.51	0.13	0.11
In-from-Other	-0.01	-0.11	0.92	-0.01	0.12	1.15	0.25	0.09
Out-to-Other	**0.26**	**2.48**	**0.01**	**0.18**	**0.32**	**3.11**	**0.00**	**0.22**
In+Out Other	0.19	1.77	0.08	0.13	**0.23**	**2.23**	**0.03**	**0.15**
Closeness	0.19	1.79	0.08	0.13	**0.23**	**2.23**	**0.03**	**0.16**
Eigenvector Centrality	**0.22**	**2.12**	**0.04**	**0.16**	**0.24**	**2.31**	**0.02**	**0.16**

Table 9: Regression coefficients, t-statistics, p-values, and Kendall τ rank-correlation coefficients for regressions of maximum loss and maximum percentage loss on systemic risk measures. Maximum loss is the dollar amount of the maximum cumulative decline in market capitalization or fund size for each financial institution during July 2007–December 2008, maximum percentage loss is the maximum loss as a percentage of the financial institution's market capitalization or total fund size in June 2007. Systemic risk measures are calculated over the October 2002–September 2005 time period. Statistics that are significant at the 5% level are displayed in bold.

We find that Out, Out-to-Other, In+Out Outer, Closeness, and Eigenvector Centrality are significant determinants of both MaxLoss and Max%Loss variables.[28] Based on the Closeness and Eigenvector Centrality variables, financial institutions that are systemically important and are the most interconnected are the ones that suffered the most during the Financial Crisis of 2007–2009. However, the institutions which declined the most in 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 in Table 8 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.[29]

Consistent with the empirical results of Sections 5.1–5.5, 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.

[28]For Max%Loss, all systemic risk measures are significant at 5% level. For MaxLoss, Out-to-Other, and Eigenvector Centrality are significant at 5% level and Out, In+Out Other, and Closeness are significant at 10%.

[29]We also consider other time periods after October 2002–September 2005, and the results are still significant for Out, Out-to-Other, In+Out Other, Closeness, and Eigenvector Centrality measures, especially at the beginning of 2007.

6 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 the "four L's" of systemic risk—liquidity, leverage, linkages, and losses—indirectly via econometric estimators such as serial correlation coefficients, regime-switching models, and Granger-causality tests. All of our five measures capture unique and different facets of systemic risk. Return autocorrelation measures the liquidity of individual financial institutions and the entire network. Contemporaneous correlations measure pairwise linkages between financial institutions. Principal components analysis provides a broader view of connections among all four groups of financial institutions. Regime-switching captures discrete shifts in the expected returns and volatility of all four sectors. And Granger-causality networks capture the complex web of statistical relations among individual firms in the finance and insurance industries.

The complexity of the global financial system calls for a multidimensional approach to measurement of systemic risk. 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. These results are confirmed even if we investigate connections among individual financial institutions. Moreover, over the recent sample period, our empirical results suggest that the banking and insurance sectors may be 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. Additional empirical results for regime-switching models and Granger-causality tests with hedge-fund sub-sector indexes are contained in Sections A.3 and A.4, respectively.

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:

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

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:*

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

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

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

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, the joint probability of S_t and Z_t can be represented as follows:

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

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:

$$U_t^\star = \left[(1-S_{t-1})(1-Z_{t-1}), S_{t-1}(1-Z_{t-1}), (1-S_{t-1})Z_{t-1}, S_{t-1}Z_{t-1}\right]',$$

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:

$$H_{S \not\Rightarrow Z} \quad (S \not\Rightarrow Z): \quad \beta_2 = \beta_4 = 0\ .$$

Under $H_{S \not\Rightarrow Z}$, 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 using a Wald test or a Likelihood ratio test.

A.3 Regime-Switching Models for Hedge-Fund Sub-Indexes

In this section, we provide a more detailed discussion of the time series properties of the probability of the high-volatility state for the four hedge-fund sub-sector indexes under the two-state Markov regime-switching model (3), corresponding to the lower panel of Table 4 and Figure A.1. Global Macro strategy was characterized by a high-volatility regime in the first part of the sample (before January 2001) and then by a low-volatility regime. This break is also found by Bollen and Whaley (2009) and Fung, Hsieh, Naik, and Ramodorai (2008). Specifically, the Global Macro strategy volatility was 14.33% during the first part of the sample (1994–2000), and then reduced to 10.57% in 2001–2008. Long/Short Equity strategy was highly affected by the Asian crisis, 1998 LTCM crisis, Internet bubble, and the recent Subprime Crisis of 2007 and the Global Financial Crisis of 2008.

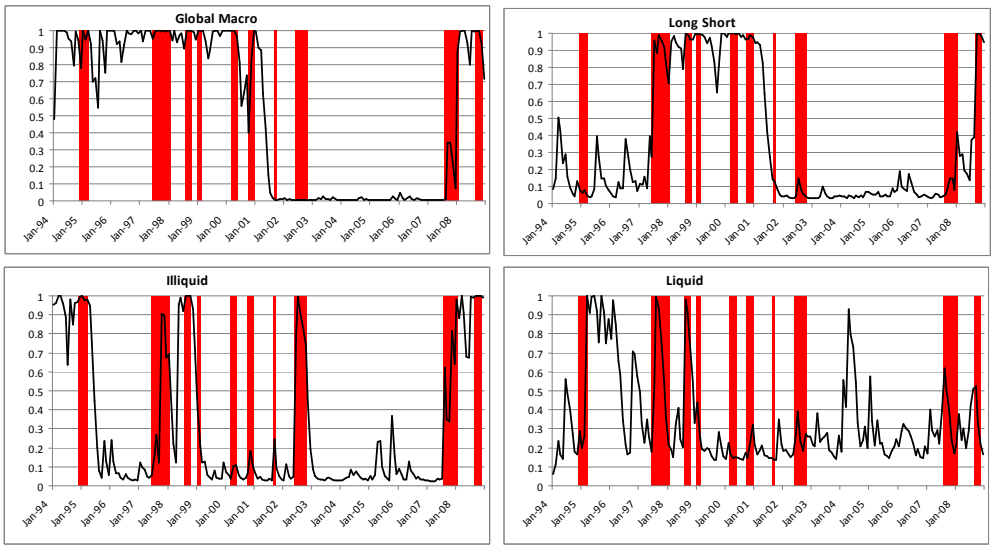


Figure A.1: Probabilities of being in the high-volatility state for the monthly return indexes of Global Macro, Long/Short Equity, Illiquid, and Liquid hedge funds, from January 1994 to December 2008. Red vertical bars represent financial crises.

Liquid strategies are affected by the Mexican, Asian, and 1998 LTCM crises. It is interesting that the effect of the Subprime Mortgage Crisis of 2007 on liquid strategies is somewhat larger (probability=0.62) than the effect of the recent Global Financial Crisis of 2008 (0.52). For other strategies, this is exactly opposite. This is consistent with Khandani and Lo (2007) finding. It is also interesting that we find a spike (0.62) in April 2004, which does not correspond to a crisis defined by Rigobon (2003), but was the start of the tightening regime of the U.S. Federal Reserve due to positive surprises in various macroeconomic indicators such as nonfarm payroll, consumption, and inflation.

Illiquid index is affected by the Mexican, Asian, LTCM crisis, WorldCom Merger and other accounting problems of 2002, the Subprime Mortgage Crisis of 2007, and the recent Global Financial Crisis of 2008. Fixed Income is one component of the Illiquid index, so it makes sense that the strategy spiked in 1994–1995 during the Federal Reserve increase of interest rates. The Illiquid index was affected through all funding crises. It is also worth noting that the probability of the high-volatility state ($Z = 1$) moves much more for the Liquid index compared to the Illiquid index due to the nature of liquid strategies. It is much easier to trade in and out of liquid assets compared to illiquid counterparts. Even if managers want to get out of illiquid strategies, they are more likely to close out liquid positions first in order to minimize market impact.

We further graph the joint probability of all four strategies being in the high-volatility state, in Figure A.2. We find that the spike in the joint probability coincides with three financial crises: Asian (probability of 0.66, October 1997), 1998 LTCM (0.98, August 1998), and the Global Financial Crisis of 2008 (0.52, September 2008). The results are consistent with those in Figure 9, except that the Internet crisis did not adversely affect hedge funds. This is consistent with results by Brunnermeier and Nagel (2004) who found that hedge funds actually captured the upturn, but reduced their positions in technology stocks that were about to decline, avoiding much of the downturn during the technology bubble of 2000.

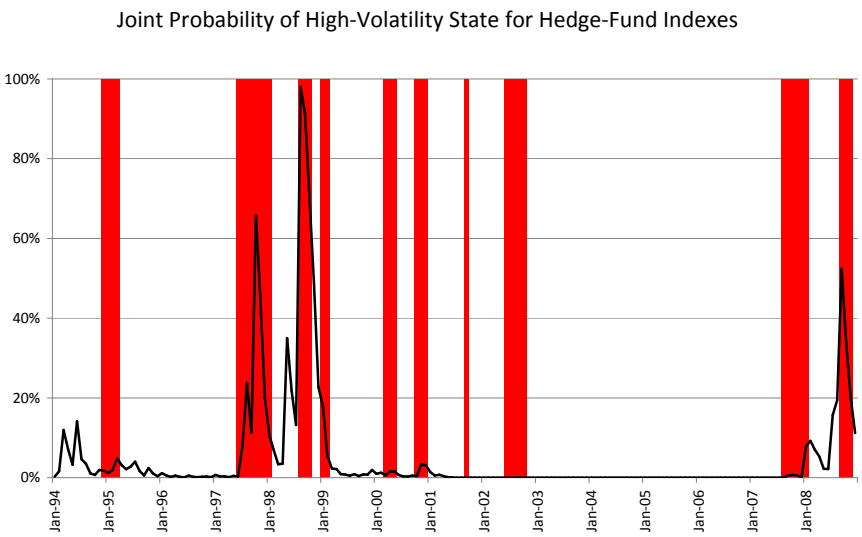


Figure A.2: The joint probability of being in the high-volatility state for the monthly return indexes of Global Macro, Long/Short Equity, Illiquid, and Liquid hedge funds from January 1994 to December 2008. Red vertical bars represent financial crises.

Finally, in Figure A.3 we graph the average probability of being in the high-volatility state for all indexes of financial institutions including the four hedge-fund indexes, i.e., our alternative systemic risk measure. All these financial institutions equally contribute to this systemic risk measure. The returns of all financial institution indexes are value-weighted. We find that during Asian and LTCM crises, Global Macro and Long/Short strategies played a large role; however, the Illiquid index started to play an ever-increasing role over time. It is interesting that during the Internet bubble, illiquidity did not play a role. Mostly the

Long/Short Equity index was affected. The Internet bubble was a speculative crisis, and not a liquidity or credit crunch that typically affects illiquid strategies. The recent 2007–2009 crisis was tied to liquidity and credit problems, which in turn adversely affected the Illiquid index. We also find that during the Enron 2002 crisis, the Illiquid index suffered. This was due to the Event Driven strategies (which are components of the Illiquid hedge-fund index) being adversely affected by decreases in merger activities, problems in distressed securities, and other issues related to Enron. Therefore, illiquid strategies are most likely to be affected during market-wide liquidity and credit dislocations. We also find that the Illiquid index moves first. For example, in August 2007, the probability of a high-volatility state for the Illiquid index moved from zero to 0.08; however, Brokers did not move much (0.04). However, in March 2008, the probability of a high-volatility state for Brokers spiked to 0.22. In conclusion, the Illiquid index is the first one to experience losses and is very well represented in the systemic risk measure in 2008, the liquidity crisis period.

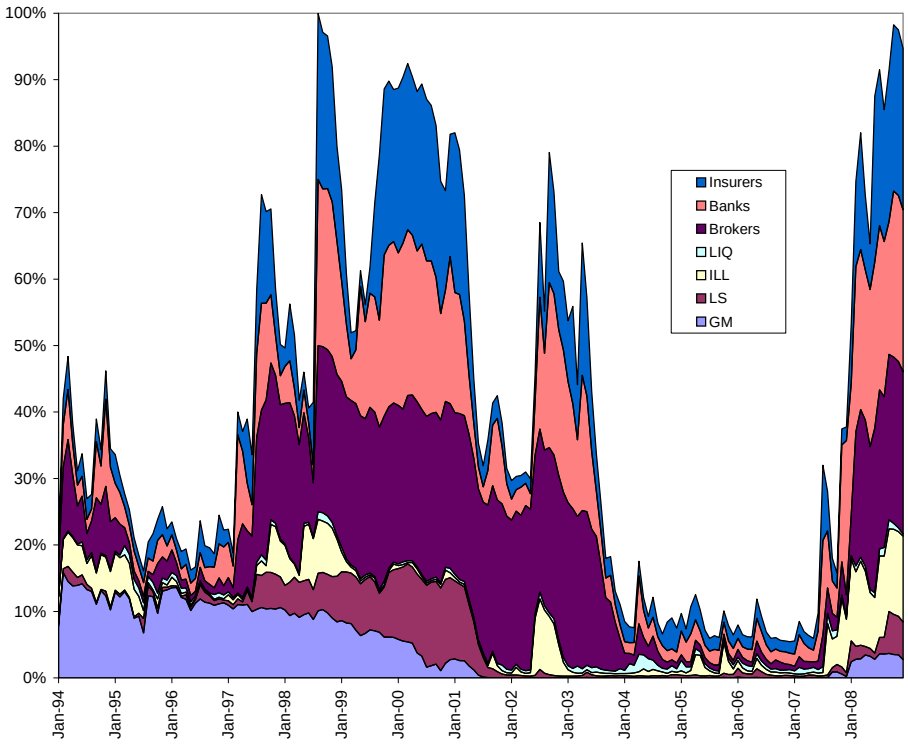


Figure A.3: The average probabilities of being in the high-volatility state for monthly return indexes of Banks, Brokers, Insurers, and four Hedge-fund indexes (Global Macro, Long/Short Equity, Illiquid, and Liquid hedge funds) from January 1994 to December 2008.

A.4 Granger Causality Tests for Hedge-Fund Sub-Indexes

Table A.1 presents the results of linear Granger causality tests for the hedge-fund indexes described in Section 4.1 using monthly returns and monthly residual returns (from regressions on the monthly returns of the S&P 500) over the same two samples: 1994–2000 and 2001–2008. Hedge-fund indexes became connected to each other and to other financial institutions

across these two samples, as measured by the percentage of pairwise causal relationships that are statistically significant at the 5% level (as a percentage of all possible pairs of relationships), which is 0% (not connected at all) in 1994–2000 and 33% in 2001–2008. In the 1994–2000 sample, the Long/Short Equity and Illiquid indexes were not affected by other financial institutions. However, in 2001–2008 they were affected by all other financial institutions such as Banks, Insurers, and Brokers. Also, shocks to the Long/Short Equity (relatively liquid) strategy affected the Illiquid strategy, which is consistent with our previous result that Long/Short Equity and Illiquid strategies are correlated. The Liquid index, on the other hand, seems not to be adversely affected by the past returns of other institutions and hedge-fund indexes in all samples.

	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers	S&P 500	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers	S&P 500
Raw Returns																
	1994 to 2000								**2001 to 2008**							
Global Macro		94.8	64.6	13.9	54.2	21.8	68.7	32.5		**3.2**	37.7	65.4	35.6	37.4	68.4	35.6
Long/Short Equity	18.9		6.8	26.1	14.4	54.3	41.1	94.9	**2.1**		**0.1**	39.8	**3.1**	28.2	13.4	24.3
Illiquid Hfunds	89.6	5.9		21.1	94.8	17.3	23.2	19.9	28.9	24.6		91.4	37.0	32.7	6.2	72.8
Liquid Hfunds	26.8	73.9	42.6		64.5	77.2	59.7	83.8	30.0	5.2	73.9		29.4	8.6	16.3	14.7
Brokers	54.5	19.6	32.9	43.1		40.0	89.5	19.5	10.1	**0.0**	**0.0**	67.5		8.0	**0.9**	19.9
Banks	66.1	72.2	40.3	32.6	87.2		88.3	31.7	8.4	**0.0**	**0.0**	18.3	25.3		8.5	35.1
Insurers	29.7	47.7	13.8	33.1	44.9	5.2		85.0	**4.3**	**0.0**	**0.0**	20.0	**0.1**	**3.1**		**4.0**
S&P 500	97.9	78.1	21.1	43.4	89.0	55.2	69.1		10.7	**0.0**	**0.0**	81.7	**1.9**	6.2	**1.2**	
Residual Returns																
	1994 to 2000								**2001 to 2008**							
Global Macro		56.2	95.5	14.8	49.1	48.6	36.9	NA		48.9	85.9	91.3	56.5	95.3	92.2	NA
Long/Short Equity	5.5		94.7	41.5	**1.1**	30.8	29.6	NA	25.2		72.6	39.1	54.7	60.6	43.7	NA
Illiquid Hfunds	76.8	35.4		38.3	20.2	43.6	88.8	NA	48.7	96.9		86.9	76.6	38.3	29.7	NA
Liquid Hfunds	25.7	88.9	14.9		82.8	38.0	39.3	NA	6.0	7.4	**2.9**		43.6	91.4	95.7	NA
Brokers	11.9	62.5	16.9	93.2		33.9	48.2	NA	55.8	33.5	27.5	83.3		97.5	21.6	NA
Banks	20.0	31.5	88.4	44.1	39.7		24.0	NA	77.9	**4.3**	8.6	6.2	54.2		97.0	NA
Insurers	14.6	30.0	59.4	33.8	91.1	87.1		NA	64.0	85.6	97.2	**2.2**	6.3	73.8		NA
S&P 500	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Table A.1: p-values of linear Granger-causality test statistics for the monthly raw and residual returns (from regressions on the monthly returns of the S&P 500) of Brokers, Banks, Insurers, and the four hedge-fund indexes (Global Macro, Long/Short Equity, Illiquid and Liquid indexes) over two samples: January 1994 to December 2000, and January 2001 to December 2008. Statistics that are significant at the 5% level are shown in bold. All p-values are adjusted for autocorrelation and heteroskedasticity.

Using raw returns, none of the hedge-fund strategies affected other financial institutions in 2001–2008 except Long/Short Equity strategy affecting future returns of Brokers. The role of the S&P 500 in the dynamics of hedge-fund indexes has also increased over time. During 1994–2000, the past returns of the S&P 500 did not affect any hedge-fund strategies, financial and insurance institutions. However, over time the past returns of the S&P 500 affected Long/Short Equity and Illiquid Hedge Funds, Brokers, and Insurers. During 1994–

2000, shocks to financial institutions had no effect on the S&P 500; however in the 2001–2008 sample, shocks to Insurers directly affected the S&P 500. Therefore, the S&P 500 and financial institutions became more tightly linked, possibly contributing to an amplification of the propagation of financial booms and distress, i.e., systemic risk.

Table A.1 also presents results for monthly residuals for all hedge-fund indexes and financial institutions. In both samples, past returns of financial institutions did not affect the future returns of other financial institutions except for the effect of the Long/Short Equity index on Brokers in 1994–2000. During 2001–2008, the Liquid hedge-fund index affected the Illiquid hedge-fund index. During 1994–2000, the Long/Short Equity index was not affected at all by the past returns of other hedge-fund indexes and financial institutions. However during 2001–2008, shocks to Banks negatively affected the Long/Short Equity index, but the Liquid hedge-fund index is not affected by any hedge-fund index in either sample and, is only affected by Insurers in 2001–2008.

Similar to results in Table 5 we find that Banks and Insurers are main culprits in spreading contagion to other financial institutions and hedge-fund indexes. In effect, we find that all hedge-fund indexes, even after accounting for the S&P 500, are greatly affected by shocks to the banking and insurance sector. Banks and Insurers seem to have a more significant impact—in terms of Granger causality—on Hedge Funds and Brokers than vice versa. This suggests that the "shadow hedge-fund system", i.e., the banks and insurers that take hedge-fund types of risks, is more significant for systemic risk than the "shadow banking system".

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