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Measuring Systemic Risk in the Finance and Insurance Sectors

Monica Billio, Mila Getmansky, Andrew W. Lo, and Loriana Pelizzon

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Measuring Systemic Risk in the Finance and Insurance Sectors*

Monica Billio†, Mila Getmansky‡,
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Abstract

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. Using 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. 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.

Keywords: Systemic Risk; Financial Institutions; Liquidity; Financial Crises;

JEL Classification: G12, G29, C51

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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 realized as a series of correlated defaults among financial institutions, occurring over a short time span and triggering 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 affect non-bank entities as well, such as money market funds, insurance companies, hedge funds, government-sponsored enterprises, and broker/dealers. Therefore, the starting point for regulatory reform is to develop formal measures of systemic risk, measures that capture the linkages and vulnerabilities of the entire financial system—not just those of the banking industry—and with which we can monitor and regulate the overall level of risk to the system and its ties to the real economy.

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. 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, and 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, hence we are focusing on the largest entities in our analysis. While smaller institutions can contribute to systemic risk as well,[1] such risks should be most easily observed in the largest entities by definition.

In the absence of direct information concerning the leverage of and linkages among these financial institutions, much of which is currently proprietary and not available to any single regulator, statistical relationships can yield valuable indirect information about the build-up of systemic risk. Moreover, even if regulatory reforms eventually require systemically

[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.

important entities to divulge 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.

Given the complexity of the global financial system, it is unrealistic to expect that a single measure of systemic risk is sufficient. A more plausible alternative is a collection of measures, each designed to capture certain aspects of the "four L's" of systemic risk—liquidity, leverage, linkages, and losses. In particular, we construct measures based on: (1) correlations; (2) return illiquidity; (3) principal components analysis; (4) regime-switching models; and (5) Granger causality tests. The motivation for these measures is to capture the kind of systemic events that created so much market dislocation in August 1998, August 2007, and the Financial Crisis of 2007–2009.

The theoretical underpinnings and institutional mechanisms by which correlation, illiquidity, and sudden changes in regime combine to produce systemic risk are now becoming 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 to reduce leverage, which can lead to systemic events as we have witnessed over the past two 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, ultimately, increased unemployment and recession as financial institutions de-leverage. Of course, 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.

Our choice to 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 had little to do with

[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).

hedge funds until recently. However, as they moved more aggressively into non-core activities such as insuring financial products, credit-default swaps, derivatives trading, and investment management, insurers created new business units that competed directly with banks, hedge funds, and broker/dealers. These activities have potential implications for systemic risk when conducted on a large scale (see Geneva Association, 2010). Similarly, the banking industry has been transformed over the last 10 years, not only with the repeal of the Glass-Steagall Act in 1999, but also through financial innovations like securitization that have blurred the distinction between loans, bank deposits, securities, and trading strategies. The types of business relationships between these sectors have also changed, with banks and insurers providing credit to hedge funds but also competing against them through their own proprietary trading desks, and hedge funds using insurers to provide principal protection on their 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 from time to 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 in 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: banks seem to have more significant impact—in terms of Granger causality—on hedge funds, insurers, and brokers than vice versa. We also find that this asymmetry became highly significant just before 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 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 are more sensitive to Value-at-Risk changes through their capital requirements (Basel 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) provide a thorough survey of the systemic risk literature, and provide the following definitions for systemic risk and systemic risk 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 systemic risk literature falls loosely into three groups. The first group concentrates on bank contagion, and these studies are 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 described 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) investigates similarities in bank trading risk, and Bartram, Brown, and Hund (2007) use 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.

After the Subprime Mortgage Crisis of 2007, many studies of systemic risk in the banking sector have been performed. For example, the Bank of England study (Aikman et al., 2009) investigates 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) propose 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 systemic studies 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) use the prices of indexed credit derivatives to extract market expectations about the nature and magnitude of credit risk in financial markets. The authors extract the "systemic credit risk" component from index credit derivatives and find that systemic risk during the 2007–2009 financial crisis is double that of the May 2005 auto-downgrade credit crisis. De Nicolo and Lucchetta (2009) investigate the impact and transmission of structurally identifiable shocks within and between the macroeconomy, financial markets, and intermediaries,

as well as their "tail" realizations.

The third group of studies in the empirical systemic risk literature focuses on contagion, spillover effects, and joint crashes in financial markets. These studies are based on simple correlation, correlation derived from ARCH models, extreme dependence of securities market returns, and securities market co-movements not explained by fundamentals, and 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 use 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) provide a measure of correlation to correct for the correlation bias stemming from changes in volatility in contagion detection, and apply 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) introduce a new approach to evaluate contagion in financial markets based on co-incidence of extreme-return shocks across countries within a region and across regions. Boyson, Stahel, and Stulz (2009) use quantile regression and logit models to analyze co-movement among hedge-fund strategies, and find 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), and Gray and Jobst (2010) propose to use contingent claims analysis to study systemic risk.

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. Since the collapse of Long Term Capital Management (LTCM) in 1998, it has become evident that hedge funds are closely tied to

systemic risk exposures. For example, Chan et al. (2006) find that funding relationships between hedge funds and large banks that have brokerage divisions greatly contribute to systemic risk. Fung and Hsieh (2002, 2004) and Chan et al. (2006) find 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) highlights 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 has been underscored by the current financial crisis, and 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).

Our work is also related to Boyson, Stahel, and Stulz (2009) who investigate 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.

Finally, 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. They explain 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 estimate 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 introducing hedge funds as 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 portfo-

[3]Diamond and Rajan (2005) show that through exacerbating aggregate liquidity shortages bank failures

lio, 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 exposure, 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

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.

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, and they all contribute to the possibility of serial correlation in asset returns which cannot easily be "arbitraged" away precisely because of the presence of these frictions. 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.

There is another, more prosaic reason for using serial correlation as a proxy for liquidity. Let us provide an example of a hedge-fund manager. For portfolios of illiquid securities, i.e., securities that are not frequently traded and for which there may not be well-established market prices, 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 consistent 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 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 their credit simultaneously, obligors will be forced

[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.

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, and 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, insurance, 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

[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.

[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

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 estimate 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]

The independence of the four return indexes can be tested explicitly by comparing $J_{p,t}$

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 $\text{Prob}\,(E_1|E_2) > \text{Prob}\,(E_1)$, 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 $\text{Prob}\,(E_1 \cap E_2) > \text{Prob}\,(E_1)\text{Prob}\,(E_2)$, hence the product is a conservative estimate of the joint probability.

to the product of the following unconditional probabilities:

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

where:

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

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 associate 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 can be due to contagion effects or the fact that the four financial institution sectors are all exposed to the same common factor, both of which capture one 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:

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

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 critical not only to properly measure the degree of interconnectedness between financial institutions, but also to determine the direction of the relationship if there is one. One econometric measure is Granger causality, a statistical notion of causality based on forecast power. X is said to "Granger-cause" Y if past values of X contain information that helps predict Y above and beyond the information contained in past values of Y alone. The mathematical formulation of this test is based on linear regressions of Y on X and X on Y, and its application to our framework is described

in the Appendix.

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

One limitation of the classical Granger causality measure is that it 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 the Granger causality of Markov chains of financial institutions. Nonlinear Granger causality measures the effect of a Markov chain of one financial institution on a Markov chain of another financial institution. Specifically, we capture the effect of one financial institution on future mean and variance of returns of another financial institution, which should be able to detect the volatility-based interconnectedness hypothesized by Danielsson, Shin, and Zigrand (2009).

For illustration, 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, there are more funds in the TASS Tremont database—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 is consistent with the hedge-fund industry 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 (measured by 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 financial industry described in Section 4. Section 5.1 contains illiquidity and correlation measures, Section 5.2 contains the 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

[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).

better understand the implications of these Granger causality relationships, in Section 5.5 we provide simple visualizations via network diagrams.

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, Insurers, and the S&P 500 are presented in Figure 1.

We can see from Figure 1 that the autocorrelation coefficient varies considerably over time. The blue line depicts the autocorrelation coefficient for each index, and the light black lines depict two-standard-deviation bands. Hedge Fund autocorrelations increased significantly from January 2004 to January 2006, declining afterwards. However, during the 2008 crisis the autocorrelation jumped precipitously, almost doubling in October 2008

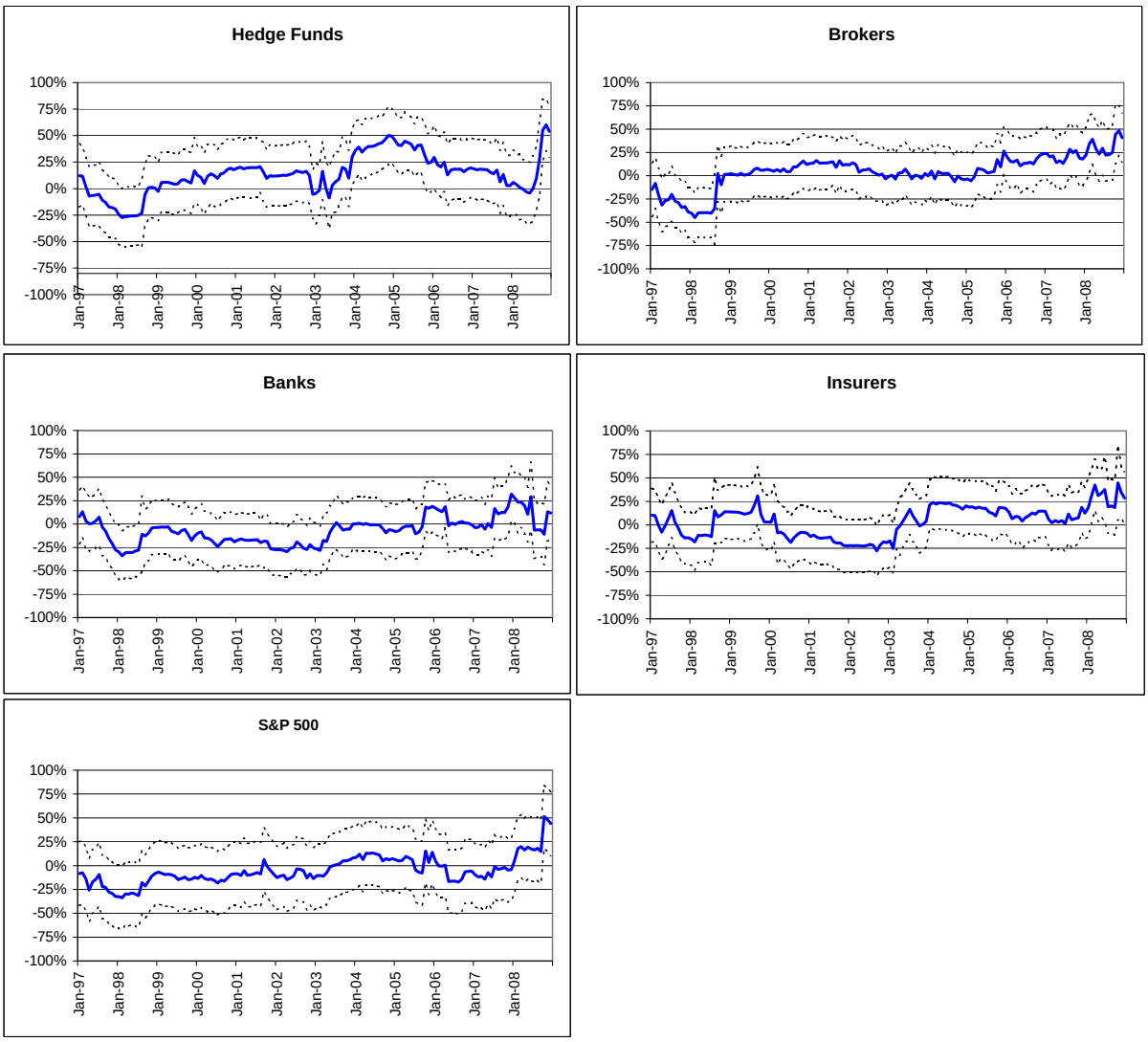


Figure 1: 36-month rolling-window autocorrelation coefficients (blue curve) and 10%-significance bands (black curves) for Hedge Funds, Brokers, Banks, Insurers, and the S&P 500 from January 1994 to December 2008.

from 0.28 to 0.55 (this change is significant at the 10% level). The autocorrelation of the Broker index was negative during the beginning of the sample period (October 1997 to July 1998), increasing afterwards but not significantly different from zero until March 2008 (0.40) and October 2008 (0.44). The autocorrelations of the Bank index are insignificantly different from zero for most of the sample, but as with the Broker index, in March 2008 the autocorrelation jumped to 0.23, then subsided during the second half of the 2008. Similarly, the autocorrelations of the Insurer are insignificant for much the sample period, but did peak in September 1999 (0.31), March 2008 (0.42) and October 2008 through the end of the sample (0.40). The S&P 500 had virtually zero autocorrelation during the entire sample except in October 2008 when it jumped to 0.51 and stayed high through the end of the sample. In conclusion, it seems that all financial institutions and the stock market experienced high autocorrelation, i.e., illiquidity during the most recent crisis period.

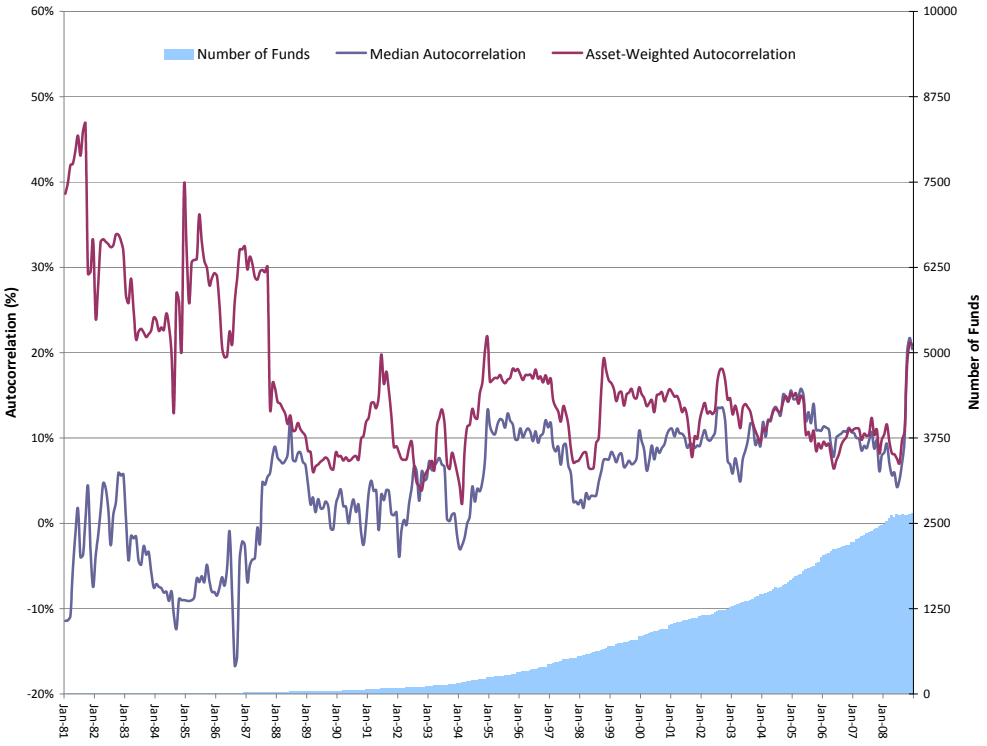


Figure 2: Monthly cross-sectional medians and asset-weighted autocorrelation coefficients of individual hedge funds, and the total number of funds in the TASS Combined hedge-fund database with at least 36 consecutive trailing months of returns, from January 1981 to December 2008.

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 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. Of course, the fact that we are using a 36-month rolling window implies that as outliers drop out of the window, correlations can shift dramatically. 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. To detect lead/lag relationships among the indexes, we also compute 12 pairs of cross-autocorrelations, 6 pairs at lag 1 (i.e., $\text{Corr}[X(t-1), Y(t)]$) and 6 pairs at lag -1 (i.e., $\text{Corr}[X(t), Y(t+1)]$). These lagged and contemporaneous correlations are plotted in Figure 3, along with crisis periods from Section 4 highlighted in gray. We find that the correlation between Hedge Funds and Brokers is high throughout the sample, generally ranging from 0.4 to 0.8. The same is true for correlations between Brokers and Banks, Brokers

and Insurers, and Banks and Insurers, with correlations ranging from 0.5 to 0.9. However, during 2000–2003 the correlation between Hedge Funds and Banks decreased sharply, as well as the correlation between Hedge Funds and Insurers. After 2003, all correlations increased. After the Subprime Crisis of 2007, the correlation between Hedge Funds and Banks decreased, possibly the result of hedge funds de-leveraging, but the correlation increased again during the Global Financial Crisis of 2008.

Figure 3: 36-month rolling-window pairwise correlations among monthly return indexes of Banks, Brokers, Insurers, and Hedge Funds. The red curve depicts contemporaneous correlations, the blue line depicts cross-autocorrelations with lagged returns for the second index, and the green line depicts cross-autocorrelations with lagged returns for the first index. Gray vertical bars represent financial crises.

After 2002, the correlations between Hedge Funds and lagged Brokers, lagged Insurers,

and lagged Banks increased. This could be related to contagion from financial institutions to hedge funds. However, this correlation may also be related to the increased autocorrelation (illiquidity) of Hedge Fund returns at the end of the sample (see Figure 1). We show below that even after adjusting for the autocorrelation of Hedge Fund returns, we still find contagion from all financial institutions to Hedge Funds. We also find that Brokers are affected by Insurers, especially during the earlier crisis periods. However, this could again be due to autocorrelation in Broker returns (see Figure 1). But even after adjusting for autocorrelated returns, we still find a positive relationship between past returns of Insurers and the returns of Brokers. Lagged Banks and Insurers are correlated with Broker returns during the LTCM 1998, 2007, and 2008 crises. We show in Section 5.4 that this is due to both the increase in causality between these financial institutions and Broker returns, and the increase in autocorrelation of Broker returns (as observed in Figure 1).

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 be magnified into systemic events. In summary, both autocorrelation (illiquidity proxy) and correlation between financial institutions serve as systemic risk measures.

We also compute correlations between financial institutions at higher leads and lags, and the results are presented in Figure 4. First, we find that Hedge Funds are significantly correlated (at the 10% level) with the first and second lags of Brokers and Banks, but only with the second lag of Insurers. Moreover, Banks and Insurers are correlated with the lag-5 returns of Brokers. We repeat this analysis for the more recent period 2001–2008 to focus on the recent crises, and the results are qualitatively consistent except that only the first lag of Brokers, Banks, and Insurers are significantly correlated with the current returns of Hedge Funds. Apparently, 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 institutions as readily.

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. The correlations between the four hedge-fund sectors have increased during the second part of the sample which is characterized by the turbulent 2007–2009 period, but Illiquid and Liquid indexes are not correlated throughout the entire sample.

Interestingly, Long/Short Equity, which is a fairly liquid strategy (its first-order auto-

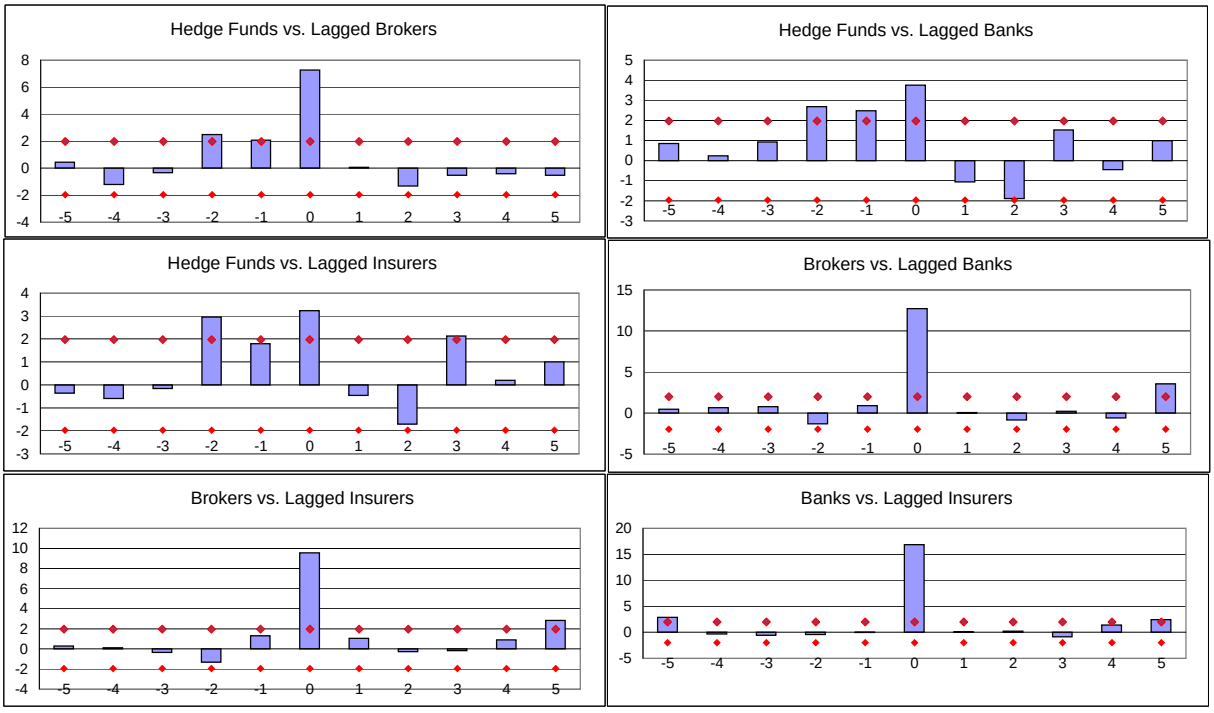


Figure 4: Contemporaneous and lagged pairwise correlations among monthly return indexes of Banks, Brokers, Insurers, and Hedge funds. Red dots indicate 90% confidence intervals.

correlation coefficient is 0.22) is uncorrelated with the Liquid index in the first part of the sample, but is highly correlated with the Illiquid index during the whole time-period. Moreover, this correlation increased over time from 0.60 (1994–2000) to 0.85 (2001–2008). 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 10% 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 PCA applied to the collection of indexes we constructed in Section 4 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.

Table 3 also contains factor loadings for these two time periods. The loadings on the first two principal components are quite persistent over time for all indexes. All loadings are significant at 10%, but we do find variation in the sensitivities of the indexes to the four principal components. For example, at 0.77, the sensitivity of the Broker returns to the first component is the largest on average, compared to only 0.12 for Hedge Funds. The sensitivity of Banks and Insurers to the first principal component is 0.47 and 0.40 on average,

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.

respectively.[11] 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. 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.

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 groupings are plausible given the various business relationships and similarities among these institutions. Hedge funds obtain leverage, clear trades, and borrow stock from brokers. Also, brokers often trade with their own accounts by implementing strategies similar to hedge funds. 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.

We also applied PCA to the four hedge-fund indexes over the same two time periods, 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, in 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, over time in 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 became more interconnected with each other over time, thus increasing systemic risk.

[11] The averages are calculated by averaging principal components for 1994–2000 and 2001–2008 periods.

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 short sell, use options, and other financial instruments that benefit both in high- and low-volatility regimes. It is also possible that a three-regime model and not a two-regime model is needed for Hedge Funds. 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 5, 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 the Hedge Funds started to increase after August 2007, spiking in March 2008 which coincided with the demise of Bear Stearns. This probability 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

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**	64.56	**0.99**	76.11	**0.97**	51.51	**0.98**	67.16
p_{11}	**0.99**	108.03	**0.97**	53.33	**0.90**	13.94	**0.87**	11.37
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**	58.07	**0.99**	103.70	**0.97**	54.66	**0.97**	31.01
p_{11}	**0.99**	111.61	**0.96**	32.43	**0.93**	21.08	**0.75**	4.41
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 10% level are shown in bold.

through the end of the sample.

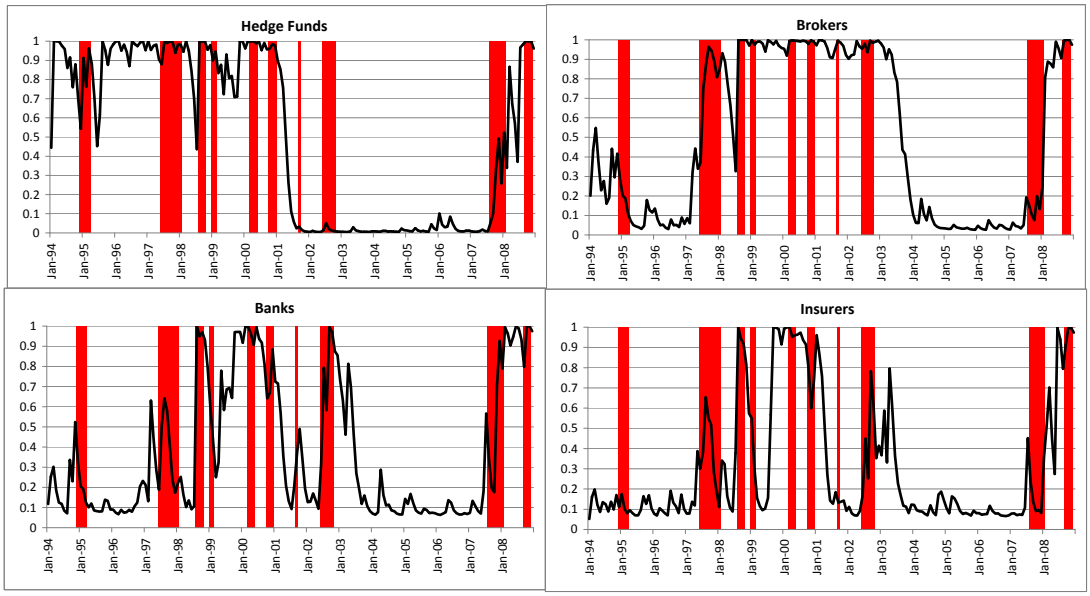


Figure 5: Probabilities of being in the high-volatility state for a two-state Markov regime-switching model for the monthly index returns of Banks, Brokers, Insurers, and Hedge Funds, from January 1994 to December 2008. Red vertical bars represent financial crises.

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. It seems that the probability declines 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 till 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 6. 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 not due to chance,

but due to some commonality in the high-volatility regimes for these financial institutions.

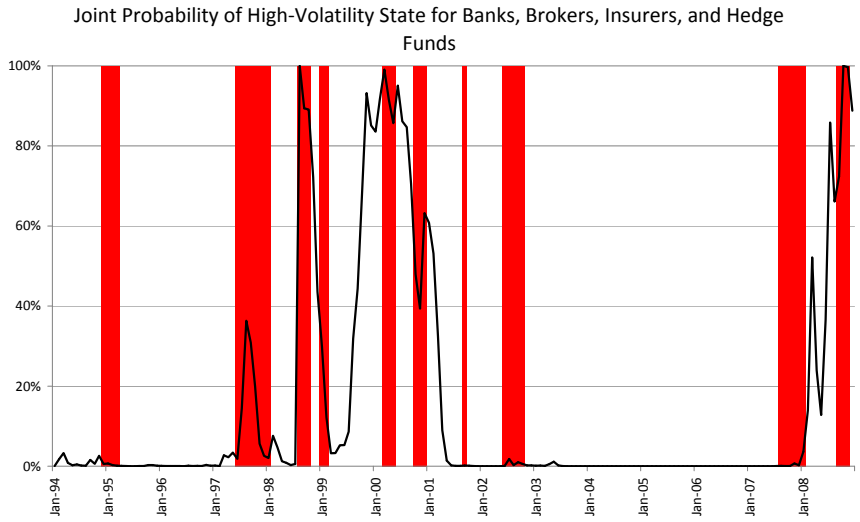


Figure 6: The joint probability of being in the high-volatility state for the monthly return indexes of Banks, Brokers, Insurers, and Hedge Funds from January 1994 to December 2008. Red vertical bars represent financial crises.

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 7. 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 prob-

ability, 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%.

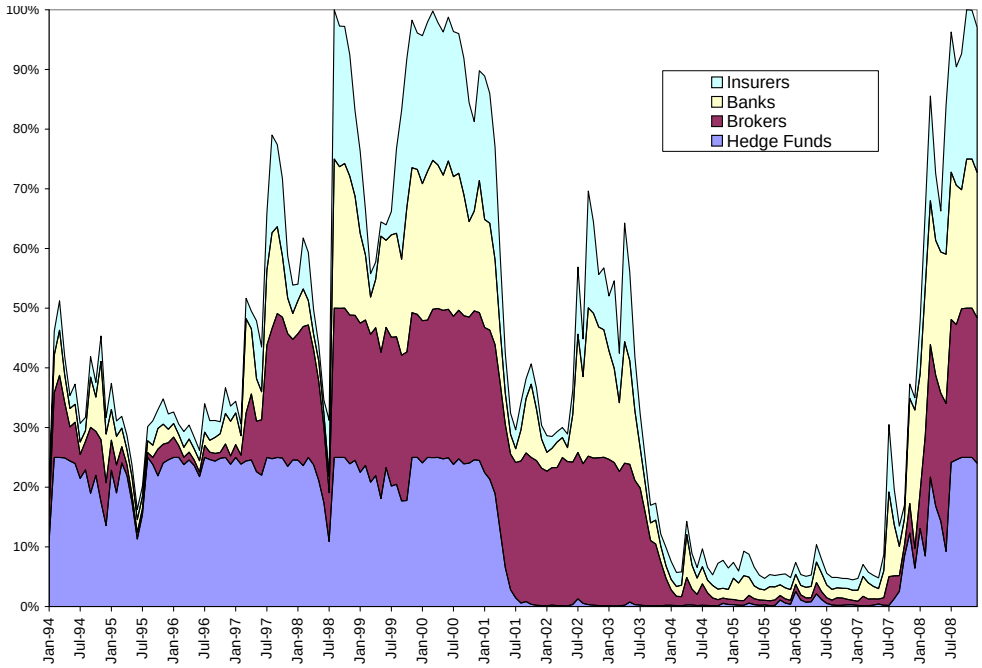


Figure 7: The average probabilities of being in the high-volatility state for monthly return indexes of Banks, Brokers, Insurers, and Hedge Funds from January 1994 to December 2008.

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, using both systemic risk measures we showed instances when systemic risk is on the rise and which financial institutions contributed the most to this increase.

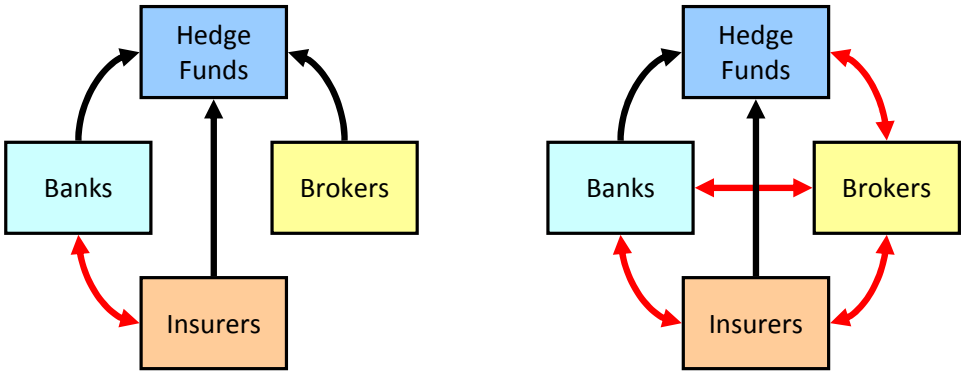
5.4 Granger Causality Tests

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 8. Relationships that are significant at the 10% level are captured with arrows. Black arrows represent uni-directional causal relationships, and red arrows represent bi-directional causal relationships. All linear Granger causality tests are adjusted for autocorrelation and heteroskedasticity.

	Hedge Funds	Brokers	Banks	Insurers	S&P 500	Hedge Funds	Brokers	Banks	Insurers	S&P 500
Raw Returns										
	1994 to 2000					**2001 to 2008**				
Hedge Funds		64.2	23.2	10.6	44.2		**2.0**	48.5	64.2	**1.9**
Brokers	**6.4**		29.0	11.4	17.3	**0.1**		**7.7**	**0.2**	**2.4**
Banks	**5.6**	65.3		**6.5**	28.0	**0.0**	**1.5**		**1.6**	**2.3**
Insurers	**4.8**	44.0	**2.8**		13.1	**0.0**	**0.1**	**2.9**		**1.9**
S&P 500	**6.8**	65.8	38.4	**5.1**		**0.0**	**0.8**	**6.0**	**0.2**	
Residual Returns										
	1994 to 2000					**2001 to 2008**				
Hedge Funds		23.6	34.9	46.3	NA		82.1	56.9	15.0	NA
Brokers	**3.0**		27.8	42.0	NA	30.0		14.4	**0.0**	NA
Banks	**1.3**	38.3		21.3	NA	**4.0**	67.5		**0.0**	NA
Insurers	**2.4**	82.9	59.8		NA	32.9	**3.5**	13.4		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 10% level are shown in bold, and p-values are adjusted for autocorrelation and heteroskedasticity.

We find that in the first part of the sample (1994–2000), Banks, Brokers, and Insurers uni-directionally affected Hedge Funds. However, shocks to Hedge Funds did not propagate to



(a) 1994 – 2000 (b) 2001 – 2008

Figure 8: Linear Granger causality relationships (at the 10% 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.

other financial institutions. Banks and Insurers had the only bi-directional relationship over this time period. We did not observe any significant causal relationships between Banks and Brokers, and Brokers and Insurers. However, in the second half of the sample (2001–2008) we find that all financial institutions became highly linked. Moreover, bi-directional relationships between Hedge Funds and Brokers, Brokers and Insurers, and Banks and Brokers emerged. In stark contrast to 1994–2000, all four sectors of the finance and insurance industry became connected in 2001–2008 (although Banks and Insurers exhibited bi-directional causality in both time periods).

In 1994–2000 we find that none of the financial institutions had any forecast power for future changes in the S&P 500 returns, but in 2001-2008 all four indexes Granger caused the S&P 500 returns.

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 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 9. We find that even after adjusting for U.S. equity exposure, financial institutions are still interconnected and propagate shocks from one financial institution to another. This result is 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 individual institution's perspective, but from a broader perspective, diversification is reduced and systemic risk is 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.

For the 1994–2000 sample, the results in Figure 9 are similar to those in Figure 8 where Brokers, Banks, and Insurers causally affect Hedge Funds. In both instances, the causality is not symmetric. However, the bi-directional relationship between Banks and Insurers is apparently explained by the S&P 500, because this relationships does not exist for the residuals of these two indexes.

In the second part of the sample (2001–2008), we find that financial institutions became more linked even after adjusting for the common exposure to the S&P 500. Whereas in 1994–2000 all causal relationships were uni-directional, we find bi-directional causality between Brokers and Insurers in 2001-2008. Additionally, Banks affect Insurers. After adjusting for the S&P 500, we find that shocks to Banks propagate to other financial institutions; however, shocks to other financial institutions do not affect Banks. In this respect, Banks appear to be the most contagious of the four types of financial institutions.

This result is quite surprising given the fact that we are using heteroskedasticity- and autocorrelation-adjusted test statistics for the monthly returns of aggregate indexes. In a

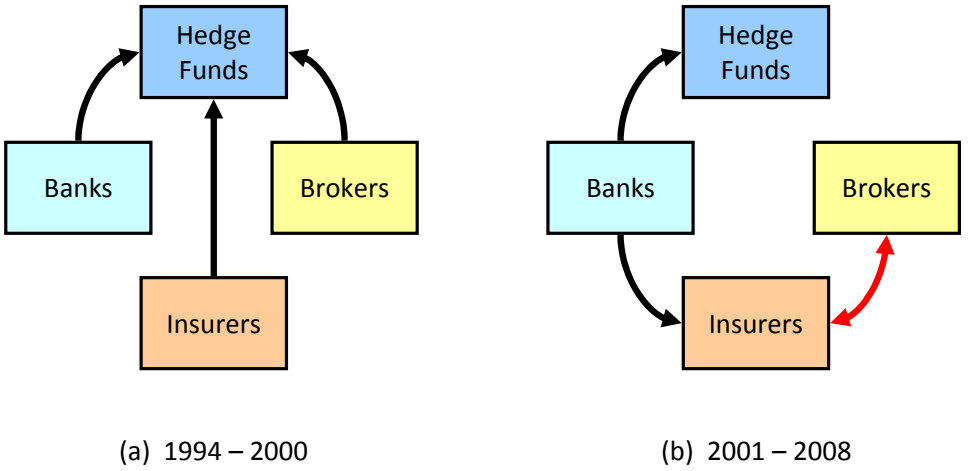


Figure 9: Linear Granger causality relationships (at the 10% level of statistical significance) among the residual returns (from a market-model regression against the S&P 500) of Banks, Brokers, Insurers, and Hedge Funds over two samples: (a) January 1994 to December 2000, and (b) January 2001 to December 2008. All p-values are adjusted for autocorrelation and heteroskedasticity.

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.

Nevertheless, our analysis is based on aggregate indexes, and it is possible that not all financial institutions 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.

	1994 to 2000							2001 to 2008						
	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers
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 10% level are shown in bold. All p-values are adjusted for autocorrelation and heteroskedasticity.

It is important to stress that linear Granger causality tests provide causality relationships based only on interconnection of means (or averages), whereas nonlinear Granger causality tests also take into account the interconnection of volatilities among financial institutions. 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 five-year sub-periods to the 25 largest institutions (as determined by average AUM during the time period considered) in each of the four index categories (Banks, Brokers, Insurers, and Hedge Funds).[12] 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 1% level are depicted,[13] and to conserve space, we show results only for five of the 11 sub-periods in Figures 10–14: 1994–1998, 1996–2000, 2000–2004, 2002–2006, and 2004–2008.[14] 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,[15] standard deviation,[16] the normalized number of connections[17], and the

[12] Given that hedge-fund returns are only available monthly, we impose a minimum of five years to obtain reliable estimates of Granger-causal relationships.

[13] Given the large number of connections between financial institutions, for this section only, we use the more restrictive 1% significance level.

[14] 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 five-year rolling-window network diagrams updated every quarter from December 1998 to December 2008, which can be viewed at `http://web.mit.edu/alo/www`.

[15] 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.

[16] 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.

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

total number of 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 1998											
All	-0.05	0.37	0.05	9%				890			
Hedge Funds	0.11	0.33	0.04	14%	6%	9%	7%	84	38	57	43
Brokers	-0.07	0.51	0.09	10%	6%	9%	7%	65	35	56	46
Banks	-0.08	0.49	0.05	11%	4%	11%	9%	68	28	65	56
Insurers	-0.03	0.34	0.05	12%	10%	8%	11%	74	63	48	64
January 1996 to December 2000											
All	-0.07	0.43	0.06	2%				175			
Hedge Funds	0.15	0.31	0.03	6%	2%	1%	1%	34	15	8	6
Brokers	-0.04	0.44	0.10	3%	1%	0%	2%	16	8	2	11
Banks	-0.06	0.53	0.07	2%	2%	1%	1%	15	15	5	8
Insurers	-0.11	0.52	0.07	2%	2%	1%	0%	11	15	4	2
January 2000 to December 2004											
All	-0.12	0.35	0.05	22%				2159			
Hedge Funds	0.24	0.14	0.01	21%	15%	23%	36%	127	91	143	223
Brokers	-0.04	0.68	0.09	21%	16%	20%	32%	129	94	125	198
Banks	-0.16	0.43	0.05	19%	14%	20%	31%	120	87	120	194
Insurers	-0.13	0.49	0.06	20%	16%	20%	27%	125	100	124	159
January 2002 to December 2006											
All	-0.06	0.33	0.03	4%				347			
Hedge Funds	0.18	0.21	0.01	8%	3%	4%	3%	45	21	22	18
Brokers	-0.05	0.62	0.06	7%	2%	2%	4%	45	13	13	24
Banks	-0.13	0.43	0.04	4%	2%	1%	1%	27	12	4	7
Insurers	0.02	0.29	0.04	5%	4%	3%	3%	30	26	21	19
January 2004 to December 2008											
All	0.12	0.35	0.05	8%				766			
Hedge Funds	0.24	0.32	0.02	9%	6%	2%	4%	56	36	15	25
Brokers	0.24	0.54	0.07	15%	7%	5%	6%	94	44	29	35
Banks	0.07	0.42	0.06	24%	6%	5%	5%	149	37	27	29
Insurers	0.15	0.32	0.06	13%	7%	4%	6%	82	44	27	37

Table 7: Summary statistics of linear Granger causality relationships (at the 1% level of statistical significance) among the monthly returns of the largest (with respect to AUM) 25 banks, brokers, insurers, and hedge funds for five samples: January 1994 to December 1998, January 1996 to December 2000, January 2000 to December 2004, January 2002 to December 2006, and January 2004 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.

We find that Granger-causality connectivity is highly dynamic among these financial institutions. For example, the total number of connections between financial institutions was 175 in 1996–2000, but it increased more than ten-fold to 2,159 in 2000–2004. We also find that during financial crises the financial system becomes much more interconnected in comparison to more tranquil periods. For example, the financial system was highly interconnected during

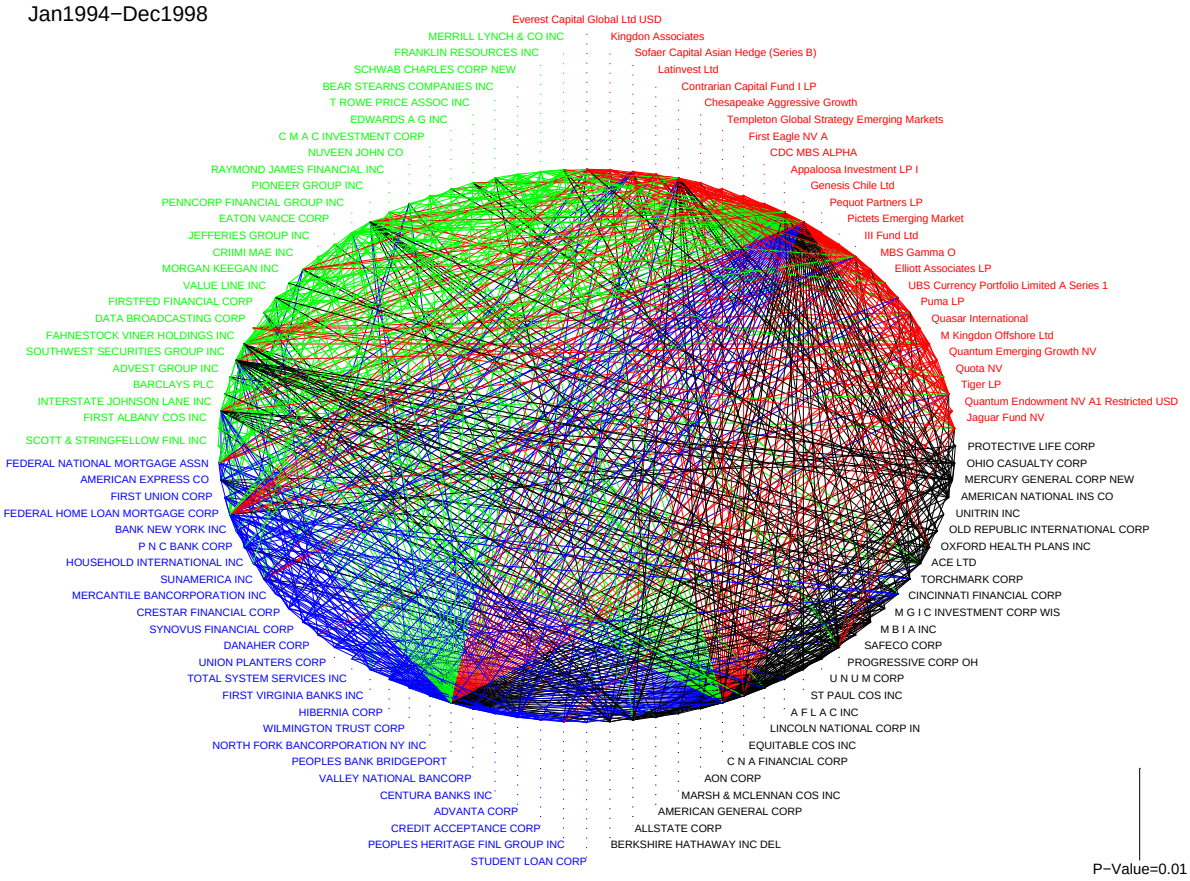


Figure 10: Network Diagram of Linear Granger causality relationships (at the 1% level of statistical significance) among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 1994 to December 1998. The type of institution causing the relationship 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.

the LTCM 1998 crisis, Internet 2000–2001 crisis, and the most recent Financial Crisis of 2007–2009. During crises a shock to one large financial institution is more likely to be propagated to other financial institutions. For example, an adverse shock to a bank can negatively impact hedge funds, insurers, and brokers. However, we also find that in the aftermath of financial distress, the interconnectedness is greatly reduced. This can be explained by several factors. First, financial institutions learn from crises, and may sever business relationships with other companies that proved to be at the root of the systemic crisis. Second, financial institutions are also more likely to "go back to basics" and stop diversifying across different financial functions in the aftermath of crises. For example, after the Financial Crisis of 2007–2009, American International Group (AIG) and other insurance companies which almost went insolvent during the crisis, are more likely to concentrate on traditional lines of business such as offering long-term care, life, and auto insurance products and disinvest from insurance policies for credit-market products which are highly interconnected with banks, hedge funds, and brokers. Third, government intervention after crises is more likely to limit the exposure of one financial institution to another. And finally, financial companies (examples are LTCM and Lehman Brothers) which are at the core of financial crises go bankrupt or are dissolved, thus eliminating previously existing financial connections.

Figures 10–14 show that prior to and during the 1998 LTCM crisis (1994–1998 period), the financial system was highly interconnected. The total number of connections stood at 890, which represents 9% of possible connections. However, in the aftermath of the crisis, the financial system became less interconnected with the normalized number of arrows at 2% in 1996–2000. Although this period contains the 1998 LTCM crisis, it also contains a substantial portion of the aftermath during which many connections were severed due to de-leveraging and risk reduction. The financial system became more linked during 2000–2004 (Internet crisis), peaking at 2,159 total connections (22% normalized). It subsequently declined to 347 (4% normalized) in the 2002–2006 period, right before the Financial Crisis of 2007–2009, and more than doubled during the recent financial crisis in the 2004–2008 period (776 total connections and 8% normalized).

By measuring Granger-causal connections among individual financial institutions, we see that during the LTCM 1998 crisis (1994–1998 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

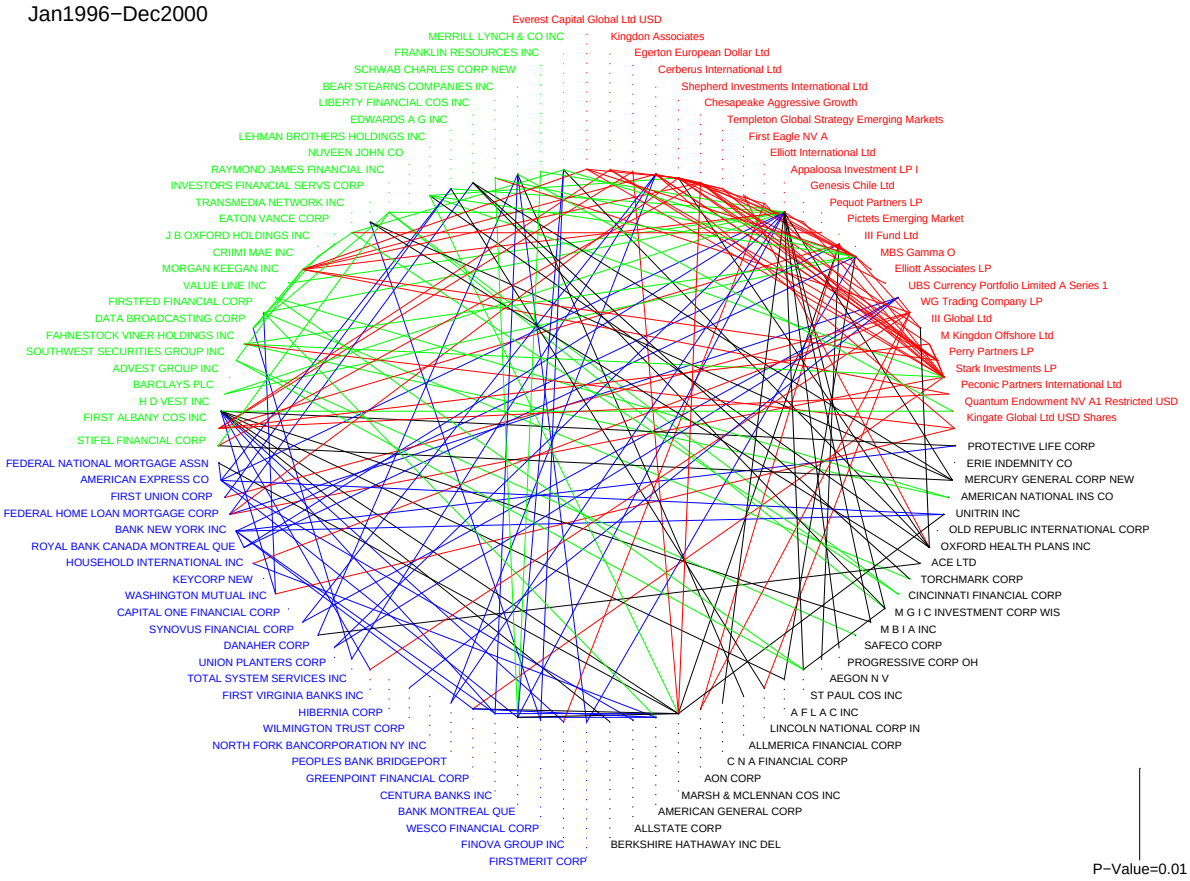


Figure 11: Network diagram of linear Granger causality relationships (at the 1% level of statistical significance) among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 1996 to December 2000. The type of institution causing the relationship 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.

on them. In the aftermath of the crisis (1996–2000), the number of financial connections decreased, especially links affecting hedge funds. During the bursting of the Internet bubble (2000–2004), all financial institutions became highly linked. In the 2002–2006 sample, the total number of connections decreased, but clearly started to increase just before and in the beginning of the recent Global Financial Crisis of 2008 (the 2004–2008 period). Hedge funds were highly affected by all other financial institutions, though they did not reciprocate in affecting brokers, banks, and insurers. The number of significant Granger causalities from banks to hedge funds was the highest (149) between these two sectors across all five sample periods. In comparison, hedge funds Granger caused only 15 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.

The beginning of the Financial Crisis of 2007–2009 is often associated with August 2007 (the "Quant Meltdown"). However, we find that the connections between financial institutions increased well before this date. For example, the number of connections doubled to 8% during April 2002–March 2007, and jumped to 20% during July 2002–June 2007. If we further investigate the Granger-causal connections among individual financial institutions, we find that hedge funds, brokers, and insurance companies were causally affected by other financial institutions. Moreover, our Granger causality tests point to an important asymmetry in the connections: banks seem to have more significant impact—in terms of Granger causality—on hedge funds, insurers, and brokers than vice versa.[18]

Table 7 shows that asset-weighted autocorrelations for the overall financial system were negative for all samples; however, in 2004–2008, the period that includes the Subprime 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 negative for all other financial institutions. However, in the last sample period (2004–2008), the asset-weighted autocorrelations became positive for all financial institutions. Asset-weighted correlations vary, peaking during the 1998 LTCM crisis and the recent Subprime Crisis of 2007 and the Global Financial Crisis of 2008. Asset-weighted monthly standard

[18]The Granger-causality results for April 2002–March 2007 and July 2002–June 2007 are omitted to conserve space, but are available from the authors upon request.

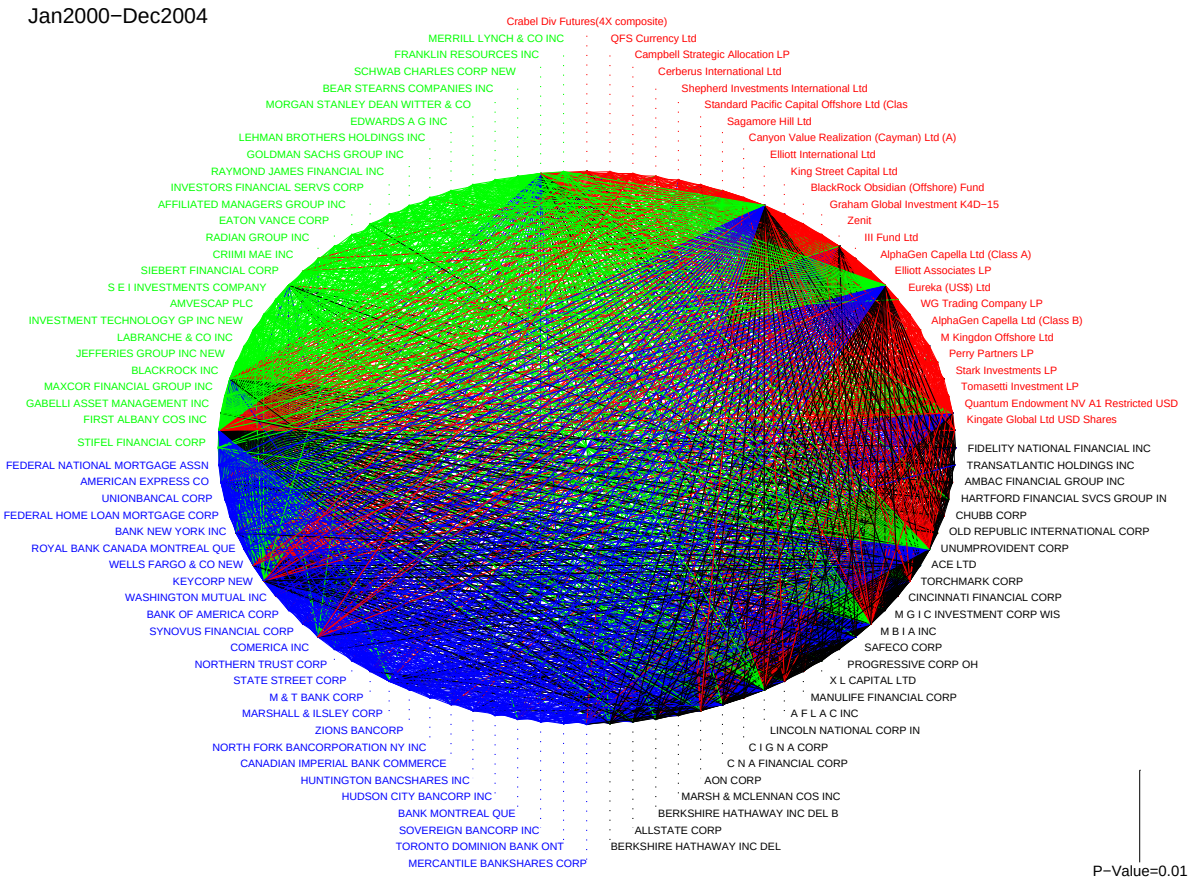


Figure 12: Network diagram of linear Granger causality relationships (at the 1% level of statistical significance) among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 2000 to December 2004. The type of institution causing the relationship 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.

deviations have been relatively stable, ranging between 3% and 5%. In summary, we find that all four have become highly interrelated and generally less liquid over the past decade, increasing the level of systemic risk in the finance and insurance industries.

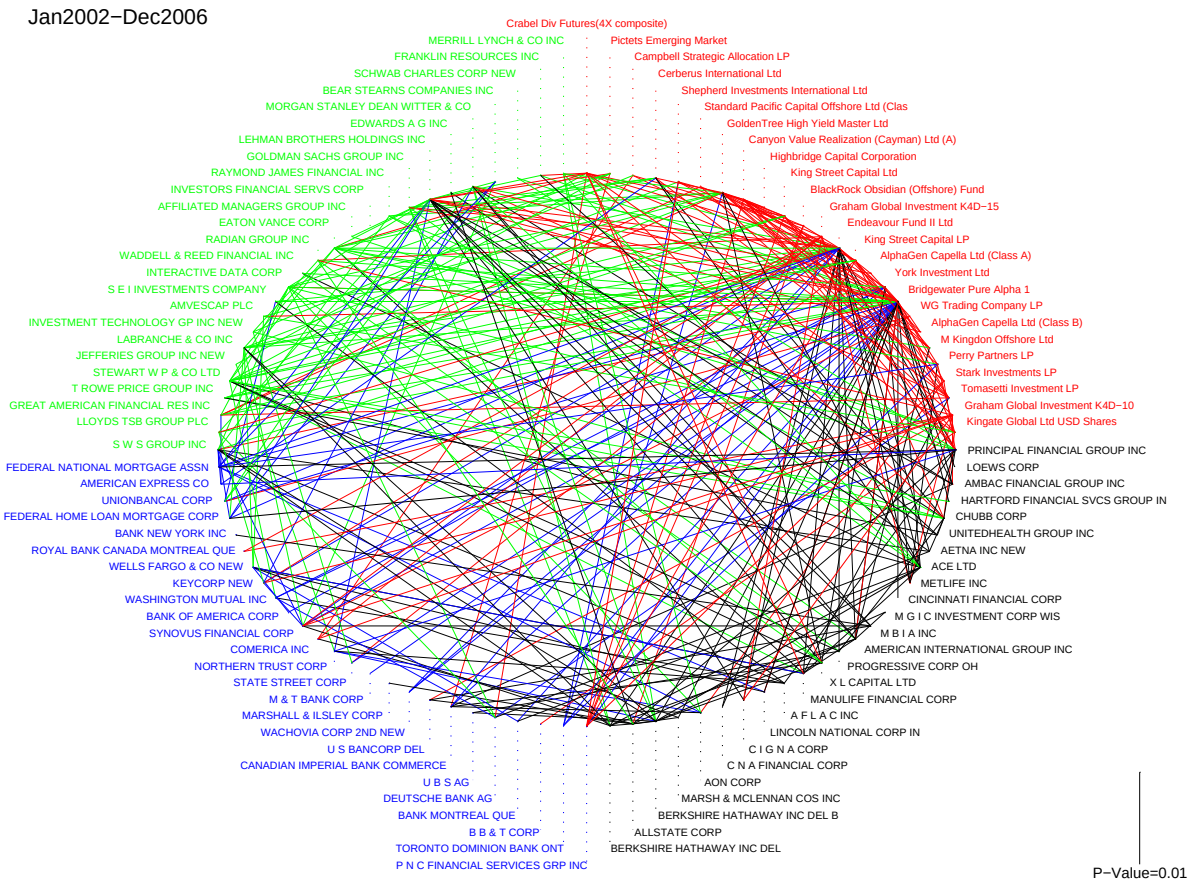


Figure 13: Network diagram of linear Granger causality relationships (at the 1% level of statistical significance) among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 2002 to December 2006. The type of institution causing the relationship is indicated by color: green for brokers, red for hedge funds, black for insurers, and blue for banks. All p-values are adjusted for autocorrelation and heteroskedasticity.

To separate contagion and common-factor exposure, we regress each company's monthly returns on the S&P 500 and re-run the linear Granger causality tests on the residuals. We 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.[19]

[19]Network diagrams for residual returns (from a market-model regression against the S&P 500) are avail-

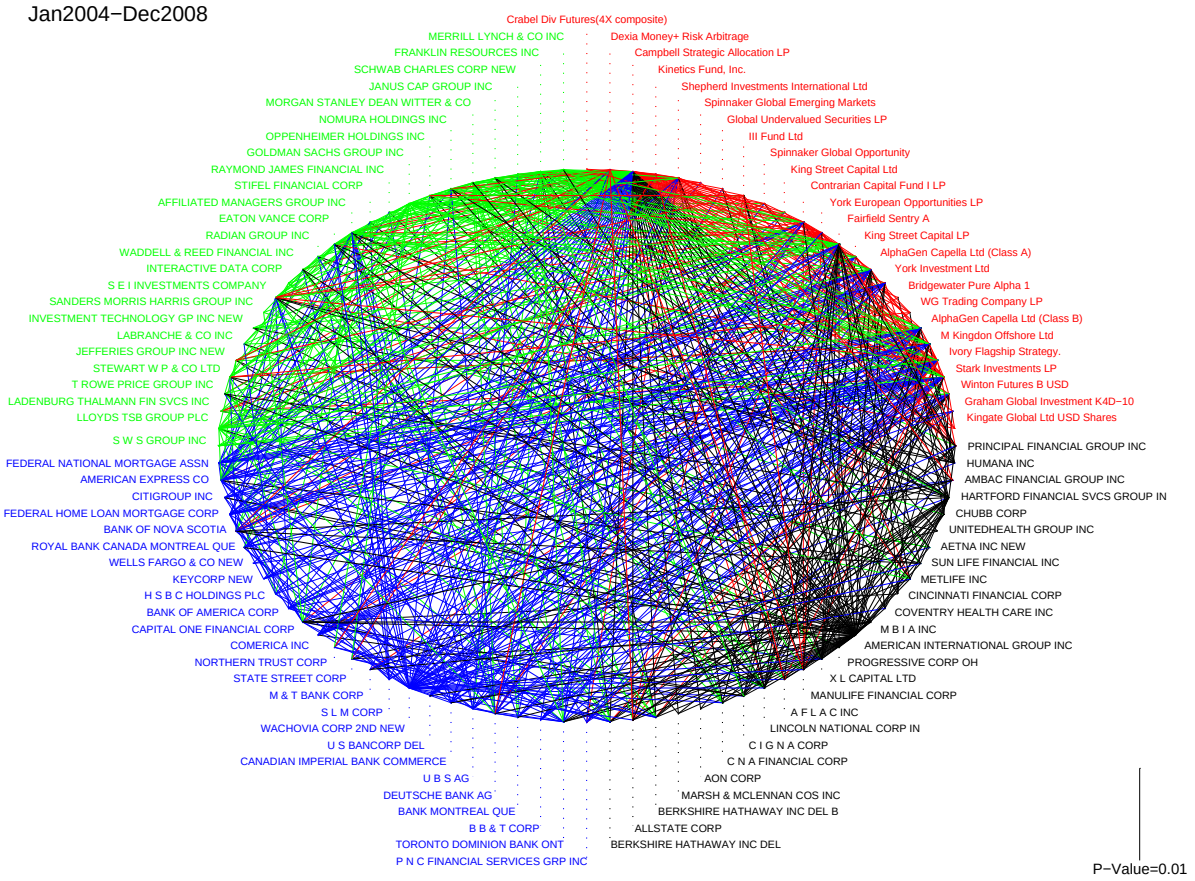


Figure 14: Network diagram of linear Granger causality relationships (at the 1% level of statistical significance) among the monthly returns of the 25 largest (in terms of average AUM) banks, brokers, insurers, and hedge funds over January 2004 to December 2008. The type of institution causing the relationship 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.

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. Using monthly returns data for hedge-fund indexes and portfolios of publicly traded banks, insurers, 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 sector may be a more importance source of systemic risk than other parts, which is consistent with the anecdotal evidence from the current financial crisis. The illiquidity of bank assets, coupled with fact that banks are not designed to withstand rapid and large losses (unlike hedge funds), makes this sector a natural repository for systemic risk. More refined measures based on data from individual institutions will likely be even more informative, and we are currently exploring such alternatives in ongoing research.

Given the complexity of the global financial system, it is unrealistic to expect that a single measure of systemic risk will suffice. 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

able upon request.

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.

The same feedback effects and dynamics apply to bank capital requirements and risk management practices based on VaR. These requirements and practices ensure the soundness of individual financial institutions; however, at the aggregate level, they may amplify aggregate fluctuations. 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 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 Non-Linear 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.

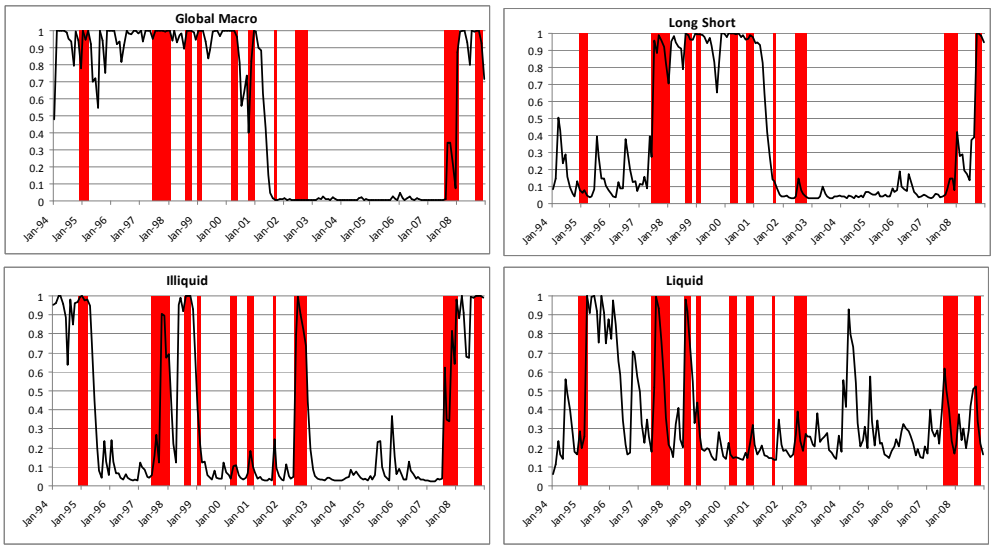


Figure A.1: Probabilities of being in the high-volatility state for the monthly return indexes of Global Macro, Long/Short Equity, Illiquid, and Liquid hedge funds, from January 1994 to December 2008. Red vertical bars represent financial crises.

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 6, 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.

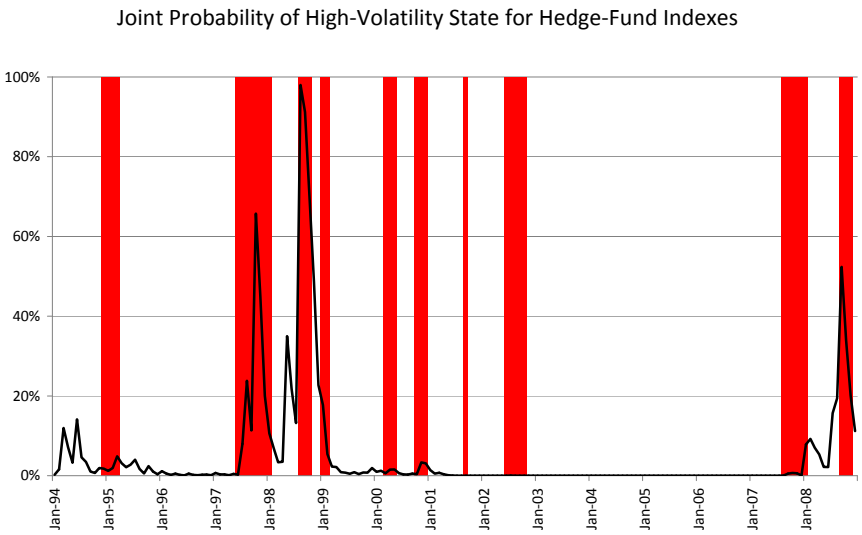


Figure A.2: The joint probability of being in the high-volatility state for the monthly return indexes of Global Macro, Long/Short Equity, Illiquid, and Liquid hedge funds from January 1994 to December 2008. Red vertical bars represent financial crises.

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.

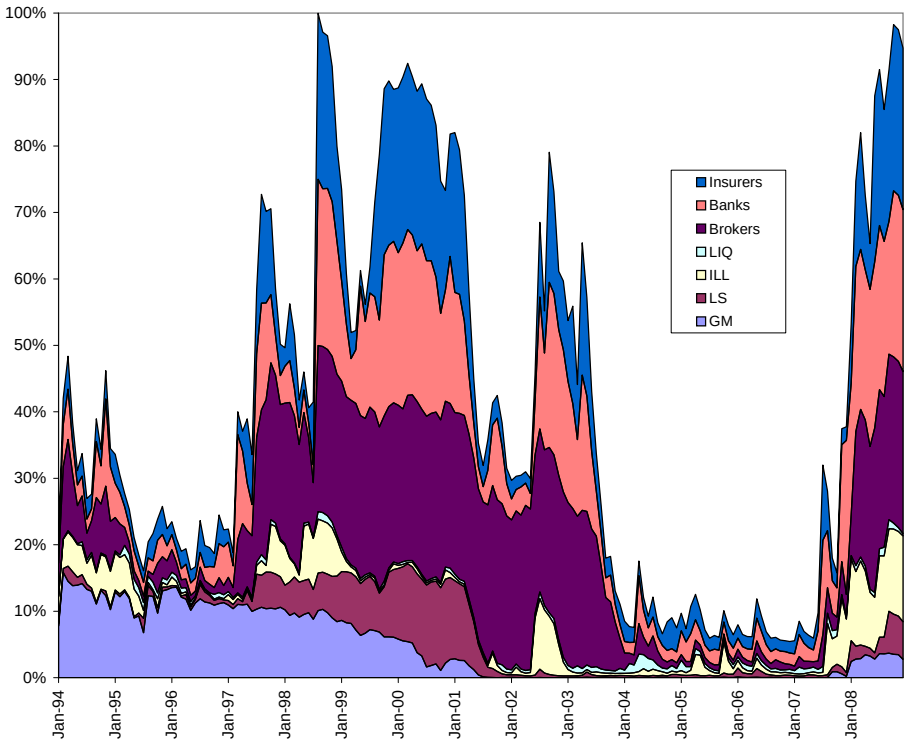


Figure A.3: The average probabilities of being in the high-volatility state for monthly return indexes of Banks, Brokers, Insurers, and four Hedge-fund indexes (Global Macro, Long/Short Equity, Illiquid, and Liquid hedge funds) from January 1994 to December 2008.

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 more 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 10% (as a percentage of all possible pairs of relationships), which is 31% in 1994–2000 and 64% in 2001-2008. If we consider bi-directional relationships, only 10% were statistically significant during the 1994–2000 sample, compared to 38% over the 2001–2008 sample. In both samples, all other hedge-fund indexes and financial institutions affected the Global Macro index. However, the relationship is not reciprocal—shocks to this index do not tend to propagate to other hedge-fund indexes or financial institutions. In the 1994–2000 sample, the Long/Short Equity index was only affected by the Illiquid index and Brokers, and the Illiquid index was not affected by other hedge-fund indexes and financial institutions. However, over time shocks to the Long/Short Equity index and all other financial institutions negatively affected this index, 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.

Raw Returns

1994 to 2000

	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers	S&P 500
Global Macro		14.1	26.1	12.6	45.8	16.4	12.3	28.8
Long/Short Equity	**3.7**		31.0	23.6	**1.6**	37.8	**7.1**	19.4
Illiquid Hfunds	**9.8**	**4.6**		19.0	67.1	13.1	**5.6**	17.6
Liquid Hfunds	**3.4**	25.4	21.5		53.2	48.5	59.0	66.1
Brokers	**8.0**	**9.4**	26.1	38.4		29.0	11.4	17.3
Banks	**8.5**	24.4	33.8	29.3	65.3		**6.5**	28.0
Insurers	**5.6**	24.7	21.5	29.7	44.0	**2.8**		13.1
S&P 500	**9.6**	10.8	33.6	38.7	65.8	38.4	**5.1**	

2001 to 2008

	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers	S&P 500
Global Macro		**1.4**	36.8	46.7	**1.5**	36.0	59.9	**1.7**
Long/Short Equity	**0.7**		**0.0**	30.6	**1.3**	27.1	64.1	**2.4**
Illiquid Hfunds	**7.6**	**8.7**		56.1	**2.0**	31.5	26.0	**2.2**
Liquid Hfunds	**7.9**	**1.7**	73.1		**1.2**	**8.2**	21.0	**0.8**
Brokers	**3.0**	**0.6**	**0.0**	47.8		**7.7**	**0.2**	**2.4**
Banks	**2.5**	**0.1**	**0.1**	14.6	**1.5**		**1.6**	**2.3**
Insurers	**1.3**	**0.7**	**0.5**	11.9	**0.1**	**2.9**		**1.9**
S&P 500	**3.1**	**0.6**	**0.0**	53.6	**0.8**	**6.0**	**0.2**	

Residual Returns

1994 to 2000

	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers	S&P 500
Global Macro		37.7	43.2	21.7	21.8	35.2	33.3	NA
Long/Short Equity	18.0		41.9	32.4	**0.4**	21.7	26.8	NA
Illiquid Hfunds	11.2	25.3		28.9	**9.6**	37.6	62.7	NA
Liquid Hfunds	**3.4**	37.4	10.0		28.3	29.2	32.7	NA
Brokers	**3.1**	37.6	10.4	70.5		27.8	42.0	NA
Banks	**4.2**	16.8	42.1	41.8	38.3		21.3	NA
Insurers	**4.2**	18.3	35.0	31.1	82.9	59.8		NA
S&P 500	NA	NA	NA	NA	NA	NA	NA	NA

2001 to 2008

	Global Macro	Long/Short Equity	Illiquid Hfunds	Liquid Hfunds	Brokers	Banks	Insurers	S&P 500
Global Macro		11.3	**2.6**	68.8	66.3	14.0	14.8	NA
Long/Short Equity	12.9		**4.0**	65.6	48.1	13.3	**0.0**	NA
Illiquid Hfunds	46.0	45.2		59.4	82.5	10.3	**0.0**	NA
Liquid Hfunds	**3.3**	**2.2**	**0.8**		33.8	14.0	15.2	NA
Brokers	41.6	**8.5**	**3.5**	95.0		14.4	**0.0**	NA
Banks	42.4	**1.3**	**0.5**	**4.6**	67.5		**0.0**	NA
Insurers	26.2	15.0	**3.6**	**1.6**	**3.5**	13.4		NA
S&P 500	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 10% level are shown in bold. All p-values are adjusted for autocorrelation and heteroskedasticity.

Using raw returns, all hedge-fund strategies affected Brokers over 2001–2008. However,

only Long/Short Equity and Illiquid indexes Granger-caused Insurers during 1994–2000. Banks are only affected by the past returns of the Liquid hedge-fund index during 2001–2008. 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 affected only Global Macro and Insurers, not other financial institutions or hedge-fund indexes. However, over time the past returns of the S&P 500 affected all hedge-fund indexes (except the Liquid hedge-fund index) and all financial institutions. During 1994–2000, shocks to financial institutions had no effect on the S&P 500; however in the 2001–2008 sample, shocks to any financial institution or hedge-fund index 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 the 1994–2000 period, all financial institutions and only Liquid strategies affected the Global Macro index. However, Global Macro was not causally linked to these other indexes. During 2001–2008, only Liquid hedge-fund index affected Global Macro. 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 Liquid hedge-fund index, Brokers, and Banks negatively affected the Long/Short Equity index. Interestingly, in the 1994–2000 sample, the Illiquid hedge-fund index was not affected by any other index or financial institution. However, in the 2001–2008 sample, this index was affected by the past returns of all other hedge-fund indexes and financial institutions. Therefore, the Illiquid index became more tightly linked with other financial institutions and hedge-fund indexes. However, the Liquid hedge-fund index is not affected by any hedge-fund index in either sample. Insurers were not affected by any financial institutions during 1994–2000. However, in the 2001–2008 sample, the past returns of Long/Short Equity, Illiquid hedge-fund index, Brokers, and Banks affected Insurer returns.

Similar to results in Table 5 we find that Banks 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 sector. Banks seem to have a more significant impact—in terms of Granger causality—on Hedge Funds, Insurers, and Brokers than vice versa. This suggests that the "shadow hedge-fund system", i.e., the banks that take hedge-fund types of risks, is more significant for systemic risk than the "shadow banking system". Banks are more interconnected with Hedge Funds than Brokers and Insurers, even after adjusting for the S&P 500.

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