Toward Determining Systemic Importance

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Abstract

We introduce a methodology for measuring systemic importance. Investors care about systemic importance because this knowledge may enable them to assess their portfolio's vulnerability to particular events and, if warranted, to pursue defensive strategies. Policymakers also need this information to ensure that policies and regulations target the appropriate entities and to engage in preventive or corrective measures more effectively when circumstances warrant intervention.

The absorption ratio, introduced by Kritzman et al. [2011], provides an implied measure of systemic risk based on principal components analysis. We extend this methodology to determine an entity's centrality. Our centrality measure captures an entity's vulnerability to failure, its connectivity to other entities, and the risk of the entities to which it is connected. We convert this measure of centrality into a measure of systemic importance by conditioning it on periods of high systemic risk.

Toward Determining Systemic Importance

Introduction

Systemic risk is the risk that a relatively narrow shock, such as the failure of a particular company, will propagate quickly and broadly throughout the financial system and to the real economy. It is the opposite of systematic risk, which measures the extent to which movement of a broad market or economic factor imparts risk to a narrow entity such as an individual company. For many decades, investors have focused more on systematic risk as they sought to design efficient portfolios and to avoid uncompensated risks. In the wake of the global financial crisis, however, investors, as well as policymakers, have shifted their attention to systemic risk, and with good reason. It is now abundantly clear that narrow events such as Lehman Brothers' default can cause the global stock market to crash, paralyze the financial system, and cast the world economy into a deep and long recession.

Much of the recent research on systemic risk has focused on the linkages between institutions.[1] However, it is notoriously difficult—if not impossible—to observe all of these linkages directly due to opacity, private transacting, accounting manipulations, and other complicating factors. We therefore employ an alternative approach to measuring systemic risk known as the absorption ratio, which was introduced by Kritzman et al. [2011]. The absorption ratio infers whether systemic risk is high or low from the behavior of asset prices. Our goal is to extend the absorption ratio methodology to determine the systemic importance of a particular entity.

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[1] See, for example, Billio et al. [2010] and Haldane [2009].

Investors care about systemic importance because this knowledge may enable them to assess their portfolio's vulnerability to particular events and, if warranted, to pursue defensive strategies. Policymakers also need this information to ensure that policies and regulations target the appropriate entities and to engage in preventive or corrective measures more effectively when circumstances warrant intervention. We apply our methodology to a sample of industry returns for the U.S. stock market and for company returns within the U.S and global financial sectors, and we rank the systemic importance of various entities. We conclude with a summary.

The Absorption Ratio as a Measure of Systemic Risk

The absorption ratio, introduced by Kritzman, Li, Page, and Rigobon [2011; henceforth KLPR], equals the fraction of the total variance of a set of asset returns explained or "absorbed" by a fixed number of eigenvectors, as shown in equation 1.

$$AR = \frac{\sum_{i=1}^{n} \sigma_{Ei}^2}{\sum_{j=1}^{N} \sigma_{Aj}^2} \tag{1}$$

where,

$\quad$ AR = Absorption ratio

$\quad$ N = number of assets

$\quad$ N = number of eigenvectors in numerator of absorption ratio

$\quad$ σ_{Ei}^2 = variance of the i-th eigenvector

$\quad$ σ_{Aj}^2 = variance of the j-th asset

KLPR provide the following intuition regarding the absorption ratio:

[The absorption ratio] captures the extent to which markets are unified or tightly coupled. When markets are tightly coupled, they are fragile in the sense that negative shocks travel more quickly and broadly than when markets are loosely linked. When the absorption ratio is low, markets are more resilient to shocks and less likely to exhibit a system wide response to bad news.[2]

Throughout our research, we use the same parameters as KLPR to compute daily absorption ratios. We estimate covariances using a rolling 500-day window to which we apply an exponential decay with a 250-day half life. In the numerator of the ratio, we include a fixed number of eigenvectors roughly equal to 20 percent of the number of assets in our universe. KLPR show that changes in the absorption ratio reveal more about market fragility than the level of the absorption ratio. Following their methodology, we calculate a measure called the standardized shift of the absorption ratio by computing its most recent 15 day average, subtracting the previous one year average, and dividing this difference by the standard deviation of the absorption ratio over the same one year period. This calculation is shown in equation 2.

$$\Delta AR = (AR_{15 \text{ Day}} - AR_{1 \text{ Year}}) / \sigma \qquad (2)$$

where,

ΔAR = Standardized shift in the absorption ratio

$AR_{15 \text{ Day}}$ = 15-day moving average of the absorption ratio

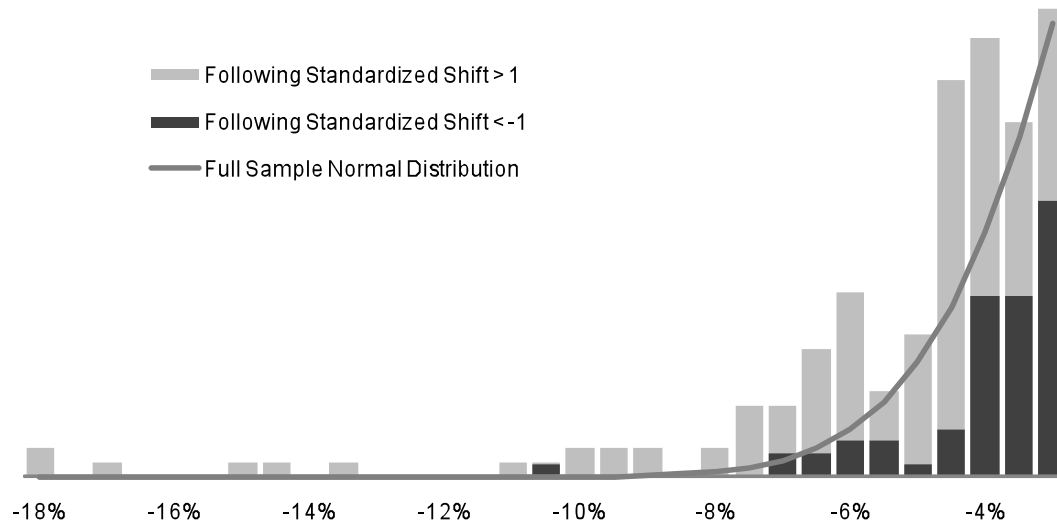$AR_{1 \text{ Year}}$ = 1-year moving average of the absorption ratio

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[2] Pukthuanthong and Roll [2009] provide a formal analysis of the distinction between average correlation and measures of integration based on principal components.

σ = standard deviation of the absorption ratio over the 1-year period

The absorption ratio may be interpreted as a measure of market fragility. KLPR show that all of the worst 1% monthly drawdowns in U.S. equities from 1998 through 2010 were preceded by a standardized shift in the absorption ratio greater than one. The authors are quick to point out that fragility by itself is not sufficient to cause market losses; however, they do find that on average stock market returns are substantially negative following absorption ratio increases and positive following absorption ratio decreases.

We performed a similar test which links the MSCI U.S. industry absorption ratio to the probability of large losses in the aggregate MSCI U.S. index. Exhibit 2 contrasts the conditional left tail of equity returns following an indication of low systemic risk with the conditional left tail following an indication of high systemic risk. The curved line shows the 10th percentile left tail, assuming normality and given the empirical mean and standard deviation of the full sample of the U.S. equity returns from January 1998 through June 2011.

Exhibit 2: Realized left tail of one-week U.S. equity returns following high and low systemic risk

Legend:
- Following Standardized Shift > 1
- Following Standardized Shift < -1
- Full Sample Normal Distribution

x-axis: -18%, -16%, -14%, -12%, -10%, -8%, -6%, -4%

* Approximately 10 percent of the full sample empirical distribution lies below -3.0 percent.

We next show how to extend the absorption ratio to determine systemic importance.

An Algorithm for Measuring Systemic Importance

To capture an asset's systemic importance, we begin by constructing a measure of centrality, which takes into account three features:

1. It captures the asset's vulnerability to failure.[3]

2. It captures how broadly and deeply an asset is connected to other assets in the system.[4]

3. It captures the riskiness of the other assets to which it is connected.

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[3] We use volatility as a proxy for vulnerability to failure.
[4] By broad we mean the number of assets to which it is correlated, and by deep we mean the strength of its correlations.

In our view, none of these features by itself is a particularly effective measure of systemic importance. For example, if a company is vulnerable to failure but not well connected, or well connected but unlikely to fail, or even vulnerable to failure and well connected, but only to companies that are themselves safe, then there is little reason to fear the failure of such a company. But collectively, these features may offer the best *observable* indication of systemic importance.

Here is how we proceed. We begin by noting a given asset's weight (as an absolute value) in each of the eigenvectors that comprise the subset of the most important eigenvectors (those in the numerator of the absorption ratio). We then multiply the asset's weight in each eigenvector by the relative importance of the eigenvector, which we measure as the percentage of variation explained by that eigenvector divided by the sum of the percentage of variation explained by all of the eigenvectors comprising the subset of the most important ones. This gives a measure of centrality, which is defined in equation 3.

$$C_i = \frac{\sum_{j=1}^{m} \left(AR^j \cdot \frac{\left| E_i^j \right|}{\sum_{k=1}^{N} \left| E_k^j \right|} \right)}{\sum_{j=1}^{m} AR^j}$$

(3)

where,

CS_i = asset centrality score

AR^j = absorption ratio of the j-th eigenvector

EV_i^j = absolute value of the exposure of the i-th asset within the j-th eigenvector

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n = number of eigenvectors in the numerator of the absorption ratio

N = total number of assets

We must also account for the relative size of each asset, because this information is not adequately reflected in securities returns. Before computing the absorption ratio or the centrality scores, we adjust the weights of the assets in our sample by multiplying each historical return by the square root of that asset's market weight from the previous day. We use the square root of market weights because large industries or companies are likely to be more connected, but at some point connectivity reaches a saturation level; hence, we assume this relationship is non-linear.[5]

In order to lend some intuition to the centrality metric, it might be helpful to think about this computation using only the first eigenvector as the numerator in the absorption ratio. This special case would be very similar to the technique used in Google's PageRank algorithm (see Brin and Page [1998]). Think of each security as a "node" on a map. By defining an "importance score" as the sum of all of its neighbors' importance scores (times some constant), that score would equal precisely the weight of the asset in the first eigenvector.[6] We instead use several eigenvectors in the numerator of the absorption ratio because most of the time several factors contribute importantly to market variance. For example, Exhibit 3 shows the explanatory power of the principal eigenvector compared to the collective explanatory power of the second through the tenth eigenvectors.

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[5] Others may prefer to use a different adjustment factor for market capitalization weights. Our findings are not highly sensitive to this choice. Other market weighting methodologies produced similar results. Furthermore, market capitalization is only one factor influencing centrality, and the centrality scores we derive are very different from capitalization weights. For example, the rank correlation of the centrality scores for the 25 largest firms in our global financial sector analysis with their respective capitalization weights is only 0.08.
[6] For additional discussion of eigenvector centrality, see Bonacich [1972].

Exhibit 3: Explanatory power of the top eigenvectors (U.S. financials absorption ratio based on individual stock returns)
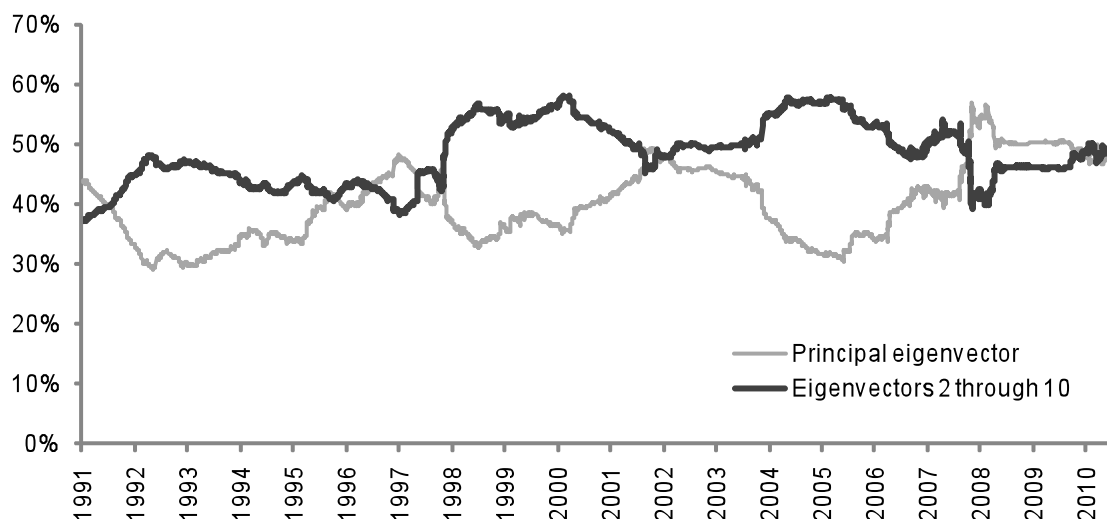
Notes: We calculate an absorption ratio using daily returns for individual stocks within the MSCI U.S. Financials index. We remove any stocks that belong to the REITs industry within the Financials sector. The absorption ratio is estimated using a rolling 500-day window, to which we apply an exponential decay with a 250-day half-life.

In order to determine systemic importance, though, we need to go a step further. Our centrality score measures the degree to which a particular asset or industry drives market variance. But we are not interested in which entities drive market variance on average across all market conditions. Rather, we wish to know which entities rise to the top when systemic risk is unusually high. We therefore average across periods only when shifts in systemic risk exceed a threshold equal to one standard deviation above average.

In the next section we present the centrality scores of selected industries and broad sectors within the U.S. stock market. Then we apply our conditioning screen to rank the systemic importance of industries within the U.S. stock market and of financial institutions within the global financial sector.

Results

We begin by applying the methodology to the MSCI U.S. GICS level 3 industries.

Exhibit 4 shows the centrality rank through time of three selected industries: commercial banks,

construction materials, and oil and gas. For ease of interpretation, we compute the percentile

rank of each industry relative to all other industries for which centrality scores were available at

that point in time.

Exhibit 4: Percentile rank of centrality score for selected U.S. industries
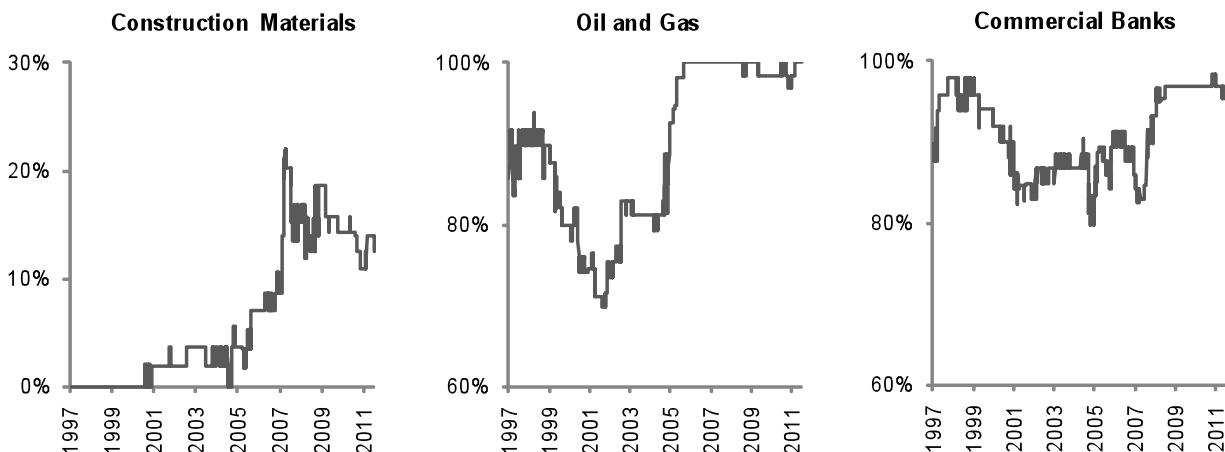
Notes: We calculate centrality scores using daily returns for MSCI U.S. GICS level 3 industries within the MSCI
U.S. index. We use a rolling 500-day window, to which we apply an exponential decay with a 250-day half-life.

These results provide comfort that our methodology for determining centrality is sensible.

It shows that a sharp rise in the centrality of the construction materials industry during the

housing bubble, and it shows that oil and gas stocks have been a primary contributor to market

variance since 2006. Finally, it shows that commercial banks drove variance during the financial crisis of the late 1990s and the more recent global financial crisis.

Exhibit 5 aggregates industry results to show the centrality scores through time for broad market sectors. The darker shades indicate relatively higher degrees of centrality. Not surprisingly, high levels of centrality for the financial, energy, and technology sectors coincide with bubbles within these sectors.

Exhibit 5: U.S. sector centrality percentile ranks
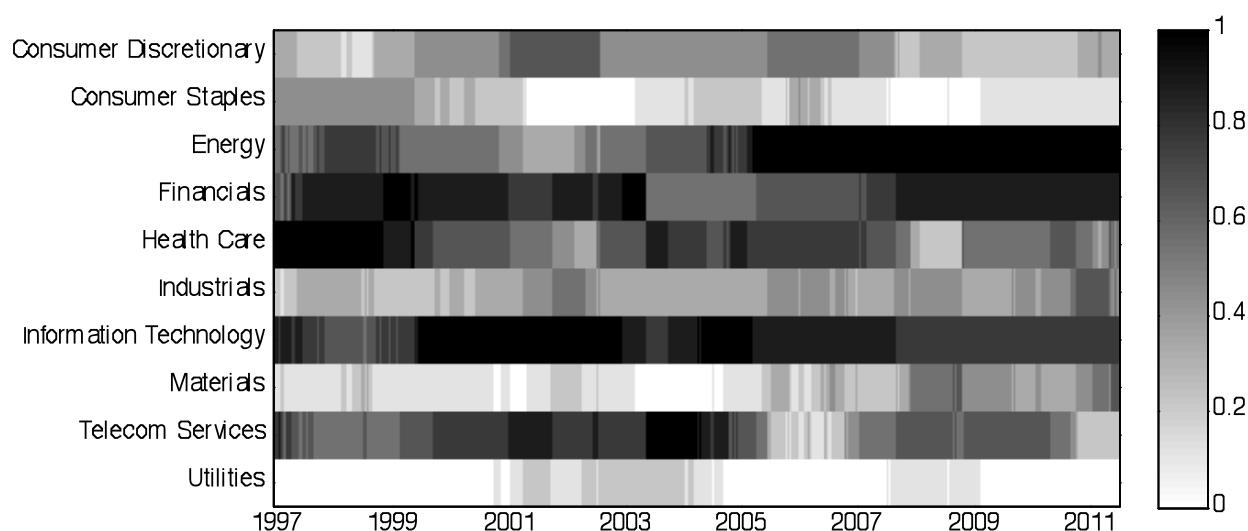
Notes: We aggregate the MSCI U.S. GICS level 3 industry centrality scores by market capitalization to obtain ten centrality scores corresponding to the MSCI U.S. GICS level 1 sectors. Next, we compute the percentile rank of each sector within the universe of ten sectors.

We now move from centrality to systemic importance. We present systemic importance as percentile ranks, which we derive as follows.

1. We first compute the absorption ratio as described earlier. Unless otherwise noted, we use a 500-day rolling window to which we apply an exponential decay with a half-life of 250 days.

2. We then identify periods of high systemic risk during which the standardized shift of the absorption ratio was equal to or greater than 1.0.

3. Finally, we compute the percentile rank of sectors, industries, and financial institutions during these periods of heightened systemic risk.[7]

Again, our measure of systemic importance deems an entity to be systemically important if it is itself inherently risky, and if it is broadly and deeply connected to other risky entities during periods of heightened systemic risk.

Exhibit 6 shows the systemic importance of U.S. sectors, which are aggregated from industry scores.

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[7] Sector centrality scores are computed as the market capitalization weighted average of the centrality scores of each industry within a given sector. This allows us to capture the information contained in the more granular industry returns data, as compared to computing centrality scores using ten broad sector indices.

Exhibit 6: Sector systemic importance, standardized shift > 1 (December 1997 – June 2011)

Top sectors when standardized shift > 1	Average percent rank
Financials	87
Information Technology	85
Energy	77
Telecommunication Services	68
Health Care	59
Consumer Discretionary	40
Industrials	37
Materials	27
Utilities	11
Consumer Staples	10

Exhibit 7 shows the 10 most systemically important U.S. industries.

Exhibit 7: Top 10 systemically important industries (December 1997 – June 2011)

Top industries when standardized shift > 1	Average percent rank
Diversified Financial Services	95
Capital Markets	94
Software	92
Commercial Banks	91
Communications Equipment	90
Oil, Gas & Consumable Fuels	90
Computers & Peripherals	90
Real Estate Investment Trusts (REITs)	87
Pharmaceuticals	85
Industrial Conglomerates	85

Exhibit 7 reveals, not surprisingly, that the most systemically important industries reside within the most systemically important sectors: financial, energy, and technology.

Next we present the same analysis for individual companies within the U.S. financial

sector. We employ the same calibration as we did in our sector and industry analyses. Exhibit 8

shows the 10 most systemically important U.S. financial companies.[8]

Exhibit 8: Top 10 systemically important U.S. financial stocks (December 1992 – June 2011)

Top U.S. financial stocks when std. shift > 1	Average percent rank
Citigroup	98
Bank of America	97
JP Morgan Chase	96
American International Group	96
Fannie Mae	93
Morgan Stanley	92
American Express	92
Merrill Lynch	91
Bank One (Acquired)	91
Goldman Sachs	89

Notes: Averages are computed over the time period for which data was available for each country.

The usual suspects populate this list, including some who merged and others whom the

government bailed out. Of particular note, though, is the absence of Lehman Brothers among the

top 10. Lehman Brothers was not always systemically important, and the list in Exhibit 8 is

based on average systemic importance over the entire sample. Lehman became systemically

important in the period leading up to the financial crisis and maintained relatively high centrality

throughout the crisis right up to its collapse, as shown in Exhibit 9.

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[8] We use the MSCI GICS classification system to identify financial stocks. We remove any stocks that belong to the
REITs industry within the Financials sector.

Exhibit 9: Lehman Brothers centrality score through time (shading represents high systemic risk within the financial sector)

15-Sep-08, 89%

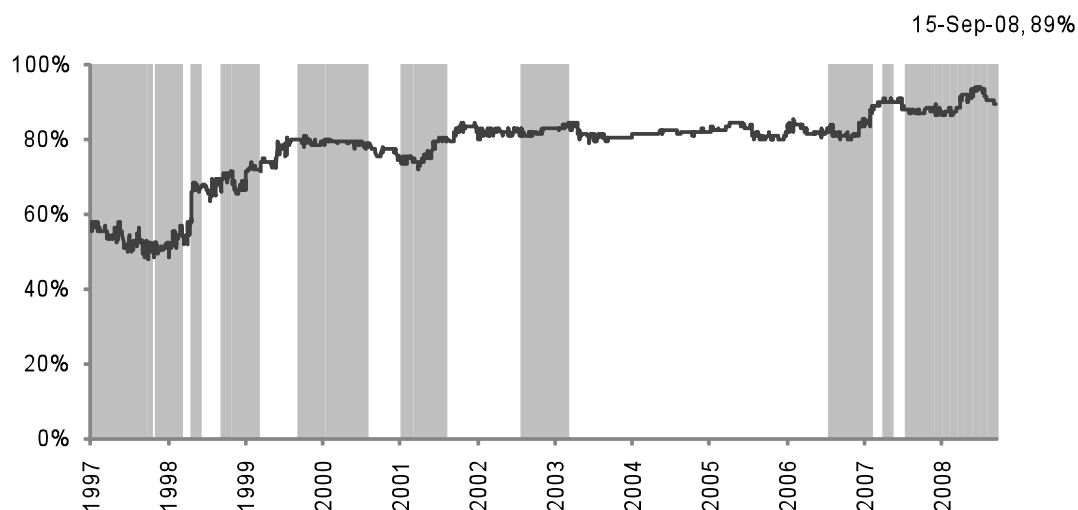Exhibit 10 offers further evidence that Lehman Brothers' centrality and systemic importance increased leading up to and throughout the global financial crisis. It shows the volatility of the first eigenvector through time constructed from a sample *that excludes Lehman Brothers*, along with the volatility of Lehman brothers. Notice the convergence that occurs as the global financial crisis unfolds.

Exhibit 10: Daily volatility over the preceding two years
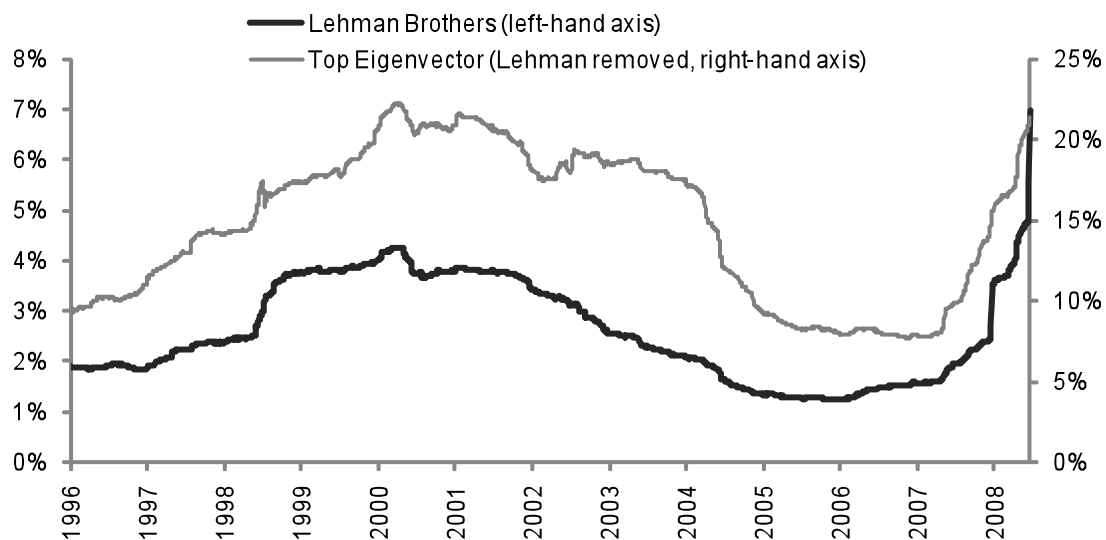
Notes: Both the eigenvector volatility and Lehman Brothers volatility are computed using the same parameters as before, including the 500-day rolling window with exponential weighting.

Next we apply our methodology to a global universe of financial stocks to measure each company's linkages with foreign firms in addition to domestic firms.[9] In this setting we use locally denominated returns to avoid introducing currency-related distortions. We also use weekly returns to mitigate the problem of asynchronous market close times across time zones.[10]

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[9] Specifically, we look at stocks comprising the MSCI World Financials index as of November 2011, excluding REITs.

[10] In order to obtain a sample of sufficient size, we use five years of weekly returns to compute covariances. We apply an exponential decay with a half life of one year. Our study covers 227 stocks. One might ask whether a sample size of 260 weekly returns is adequate to estimate eigenvectors reliably. We believe our results are robust for two reasons. First, our calculation is based exclusively on information contained in the top 20 percent of eigenvectors. These eigenvectors represent precisely the most important and stable part of the covariance matrix. In fact, a common technique for correcting poorly conditioned covariance matrices involves re-constituting the matrix based only on the most important eigenvectors. Second, we re-ran the global centrality scores while restricting our analysis to a subset of only the 50 largest stocks in our universe, which allows for a greater ratio of historical data points to number of assets. The results were nearly identical to those based on 227 stocks, with a rank correlation of 0.99.

Our approach to measuring systemic importance relies solely on the behavior of asset prices, which gives it two virtues. It is simple and thus easily updated, and it captures risks and linkages that may not be otherwise observable. It is limited, though, because it fails to consider fundamental factors that may not be embedded in security prices.

On November 4, 2011, the global Financial Stability Board (FSB) released their list of 29 global systemically important financial institutions. The FSB study is based on data as of the end of 2009, and seeks to identify "financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity." [11] They use a detailed methodology designed by the Basel Committee on Banking Supervision, which involves aggregating each institution's scores across 12 fundamental indicators.[12] Exhibit 11 highlights the differences between our methodology and the FSB's methodology.

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[11] Quotation is from the document *Policy Measures to Address Systemically Important Financial Institutions*, by the Financial Stability Board (FSB) on November 4, 2011.
[12] See document by Basel Committee on Banking Supervision, 2011 (listed in references).

Exhibit 11: Comparison to the Financial Stability Board Methodology

	Our methodology	Financial Stability Board
Data and calculation	Systemic importance scores are derived from securities price movement, using principal component analysis. This technique captures: • how broadly and deeply an institution is connected to other institutions in the system, • the institution's vulnerability to failure, and • the riskiness of the other institutions to which it is connected.	Systemic importance scores are calculated by weighting a range of fundamental factors or indicators, often from company balance sheets. The indicators used (and their weightings) are: * • Cross-jurisdictional claims (10%) • Cross-jurisdictional liabilities (10%) • Total exposures as defined by Basel III leverage (20%) • Intra-financial system assets (6.67%) • Intra-financial system liabilities (6.67%) • Wholesale funding ratio (6.67%) • Assets under custody (6.67%) • Payments cleared and settled via systems (6.67%) • Values of underwritten debt & equity trans. (6.67%) • OTC derivatives notional value (6.67%) • Level 3 assets (6.67%) • Trading book value and avail. for sale value (6.67%)
Timeliness	One week delay	Two year delay **

* See Basel Committee on Banking Supervision (2011).
** See Financial Stability Board, "Policy Measures to Address Systemically Important Financial Institutions," 4 November 2011.

Exhibit 12 shows the top 29 systemically important global financial institutions using our methodology. We use data as of the end of 2009, and we remove insurance companies and other non-bank financial institutions, to facilitate comparison with the FSB's list.

Exhibit 12: Top 29 systemically important global financial institutions (excluding insurance companies and other non-bank financial institutions, as of Dec 25, 2009)

Rank	Global financial institutions	Rank	(list continued)
1	Bank of America	16	Unicredit
2	JP Morgan Chase	17	Mitsubishi UFJ FG
3	Wells Fargo	18	Credit Suisse
4	Citigroup	19	Societe Generale
5	Barclays	20	Deutsche Bank
6	Royal Bank of Scotland	21	Credit Agricole
7	HSBC	22	Sumitomo Mitsui FG
8	Lloyds Banking Group	23	KBC
9	BNP Paribas	24	PNC
10	Goldman Sachs	25	Intesa Sanpaolo
11	Morgan Stanley	26	BBV Argentaria
12	Santander	27	Bank of New York Mellon
13	US Bancorp	28	State Street
14	UBS	29	Standard Chartered
15	ING		

☐ = also appears on the FSB's list of 29 systemically important financial institutions

It is interesting to note that our methodology, which is simply based on inferring importance from price behavior, generates very similar results to the FSB's more laborious approach. We found a substantial (79 percent) overlap between the 29 institutions identified by the FSB and the top 29 institutions we identified. In addition, all but one of the top 22 firms in Exhibit 12 is on the FSB list.

We do not argue that our approach is necessarily superior to that of the FSB. We acknowledge that it is less explicit. However, it is certainly more timely, and it may capture hidden linkages that are not apparent in fundamental data. In our view, investors and policymakers should take into account both approaches, as well as others, in assessing systemic importance.

In Exhibit 13 we present the systemic importance of global financial institutions as of November 25, 2011. It may be prudent to pay attention to the institutions listed here, especially if the appearance of any of them seems counterintuitive.

Exhibit 13: Top 25 systemically important global financial institutions (as of Nov 25, 2011)

Rank	Global financial stocks		(list continued)
1	Bank of America	14	Goldman Sachs
2	Citigroup	15	ING
3	JP Morgan Chase	16	AXA
4	Wells Fargo	17	Intesa Sanpaolo
5	BNP Paribas	18	BBV Argentaria
6	Santander	19	UBS
7	Lloyds Banking Group	20	Credit Suisse
8	Barclays	21	Credit Agricole
9	HSBC	22	Deutsche Bank
10	Royal Bank of Scotland	23	Allianz
11	Societe Generale	24	Met Life
12	Unicredit	25	US Bancorp
13	Morgan Stanley		

Exhibit 14 compares certain characteristics of the most systemically important firms to the characteristics of the global universe of financial institutions, which is listed in the appendix.

Exhibit 14: Stratification of the top 25 systemically important global financial institutions compared to the full universe of institutions (as of Nov 25, 2011)

Country	Top 25 (%)	All (%)		Region	Top 25 (%)	All (%)
Australia	0	5		Asia Pacific	0	23
Austria	0	1		Europe	68	38
Belgium	0	2		North America	32	39
Canada	0	8				
Denmark	0	1		**MSCI GICS Industry**		
Finland	0	1		Insurance	12	31
France	16	4		Diversified Financial Services	16	11
Germany	8	2		Commercial Banks	52	41
Greece	0	2		Consumer Finance	0	2
Hong Kong	0	2		Capital Markets	20	14
Israel	0	2		Thrifts & Mortgage Finance	0	1
Italy	8	4				
Japan	0	14		**Market Capitalization**		
Netherlands	4	1		50 billion USD or larger	28	8
Norway	0	0		10-50 billion USD	72	36
Portugal	0	1		5-10 billion USD	0	21
Singapore	0	2		1-5 billion USD	0	33
Spain	8	3		1 billion USD or smaller	0	2
Sweden	0	4				
Switzerland	8	4				
United Kingdom	16	8				
United States	32	31				

Exhibit 14 reveals that, relative to the global universe, systemically important financial institutions are overrepresented within Europe, the diversified financial services, commercial banks, and capital markets industries, and large institutions. These systemically important firms are underrepresented within Asia and the insurance industry.

Conclusion

We introduce a methodology for determining systemic importance that captures an asset's riskiness and connectivity to other risky assets during periods of high systemic risk.

Our empirical findings suggest, not surprisingly, that entities associated with finance, energy, and technology are the most systemically important. We also show, what is obvious by hindsight, that Lehman Brothers was one of the most systemically important financial institutions leading up to the global financial crisis. Our methodology, however, would have revealed the increasing systemic importance of Lehman Brothers nearly two years before it collapsed.

Our final analysis ranks the systemic importance of global financial institutions as of November 2011. We urge readers to heed these results, but to interpret them with due circumspection. Our measure is not an indication of an entity's financial strength or weakness, nor is it a gauge of creditworthiness or a predictor of investment performance. It is a statistical representation of an entity's vulnerability to failure and connectivity to other risky entities, derived solely from historical returns and ignoring current fundamental information.

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Appendix

Exhibit A1 extends Exhibit 13 to show the rankings of all global financial institutions included in our analysis, as of November 25, 2011.

Exhibit A1: Ranked systemically important global financial institutions (as of Nov 25, 2011)

1	Bank of America	58	Natixis	115	XL Group	172	Shinsei Bank
2	Citigroup	59	Aegon	116	Resona Holdings	173	Banca Carige
3	JP Morgan Chase	60	Lincoln National	117	Power Financial	174	Leumi
4	Wells Fargo	61	Ageas	118	M&T Bank	175	Axis Capital
5	BNP Paribas	62	Blackrock	119	Chubb	176	Investec
6	Santander	63	Fifth Third Bancorp	120	Alpha Bank	177	Singapore Exchange
7	Lloyds Banking Group	64	National Bank of Greece	121	DBS Group	178	Chiba Bank
8	Barclays	65	Regions Financial	122	Moody's	179	Baloise
9	HSBC	66	Toronto-Dominion Bank	123	T&D Holdings	180	IGM Financial
10	Royal Bank of Scotland	67	BB&T	124	Comerica	181	SBI
11	Societe Generale	68	Hong Kong Exch. & Clearing	125	Mediobanca	182	Royal & Sun Alliance
12	Unicredit	69	Tokio Marine	126	UBI Banca	183	Bank Hapoalim
13	Morgan Stanley	70	Danske Bank	127	United Overseas Bank	184	Fidelity National Financial
14	Goldman Sachs	71	Nomura	128	Standard Life	185	Old Republic International
15	ING	72	SEB	129	Unum	186	Cincinnati Financial
16	AXA	73	BOC Hong Kong	130	Intercontinental	187	Ratos
17	Intesa Sanpaolo	74	Bank of Nova Scotia	131	AMP	188	Peoples United
18	BBV Argentaria	75	Meunchener Ruck.	132	Legg Mason	189	Kinnevik
19	UBS	76	Principal Financial	133	Sumitomo Mitsui Trust	190	Shizuoka Bank
20	Credit Suisse	77	Charles Schwab	134	OCBC	191	Mitsubishi UFJ Lease & Fin.
21	Credit Agricole	78	DNB NOR	135	Groupe Bruxelles Lambert	192	Admiral Group
22	Deutsche Bank	79	Raiffeisen Bank	136	GAM	193	SCOR
23	Allianz	80	CME Group	137	Bank of Cyprus	194	Fukuoka FG
24	Met Life	81	Great West Life	138	Daiwa Securities	195	Wing Hang Bank
25	US Bancorp	82	T Rowe Price	139	Marsh & McLennan	196	Willis Group
26	AIG	83	Swedbank	140	Vienna Insurance	197	Insurance Australia Group
27	Mitsubishi UFJ FG	84	Sun Life	141	Progressive	198	Bendigo & Adelaide Bank
28	American Express	85	Keycorp	142	Power Corp of Canada	199	Partnerre
29	Prudential Financial	86	Genworth Financial	143	Banco Sabadell	200	Industrial Alliance
30	KBC Groupe	87	Allstate	144	Nasdaq OMX	201	Onex
31	PNC Group	88	Legal & General	145	Banco Espirito Santo	202	CI Financial
32	Standard Chartered	89	Hang Seng Bank	146	Jefferies	203	Hokuhoku FG
33	Bank of New York Mellon	90	Travelers	147	Swiss Life	204	W. R. Berkley
34	Manulife Financial	91	Ameriprise	148	ICAP	205	Joyo Bank
35	Sumitomo Mitsui FG	92	Banco Popular Espanol	149	Pargesa	206	Everest Real Estate
36	Berkshire Hathaway	93	Canadian Imperial Bank	150	Suncorp	207	Arch Capital
37	Westpac	94	Orix	151	Intesa Sanpaolo RNC	208	Industrivarden
38	Nordea	95	QBE Insurance Group	152	Schroders	209	Aeon Credit Service
39	State Street	96	ACE	153	BCP Banco Comercial	210	ASX
40	Capital One	97	NYSE Euronext	154	Investor	211	Bank Kyoto
41	Hartford Financial	98	Svenska Handelsbanken	155	AON	212	Suruga Bank
42	Aflac	99	Bank of Montreal	156	Eaton Vance	213	Yamaguchi FG
43	Royal Bank of Canada	100	Leucadia National	157	Bankinter	214	Hachijuni Bank
44	Aviva	101	Macquarie	158	Eurazeo	215	Nishi-Nippon City Bank
45	Suntrust	102	MS&AD Insurance Group	159	Bank East Asia	216	Aozora Bank
46	National Australia Bank	103	Sampo	160	Hudson City Bancorp	217	Israel Discount Bank
47	Commonwealth Bk of Australia	104	Man Group	161	3i Group	218	Mizrahi Tefahot Bank
48	Zurich Financial	105	SLM	162	Torchmark	219	Chugoku Bank
49	Erste Group	106	Northern Trust	163	Hannover Ruck.	220	Gunma Bank
50	Assicurazioni Generali	107	EFG Eurobank Ergasias	164	London Stock Exchange	221	Hiroshima Bank
51	Commerzbank	108	Loews	165	National Bank of Canada	222	RenaissanceRe
52	Prudential	109	Banco Popolare	166	New York Community Bancorp	223	TrygVesta
53	Franklin Resources	110	Banca Monte dei Paschi	167	Bank of Yokohama	224	Intact Financial
54	Swiss Re	111	CNP Assurances	168	Assurant	225	IYO Bank
55	Mizuho FG	112	TD Ameritrade	169	Credit Saison	226	TMX Group
56	Dexia	113	Old Mutual	170	SEI Investments	227	Fairfax
57	ANZ Banking Group	114	Mapfre	171	Pohjola bank		