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Toward Determining Systemic Importance

WILL KINLAW, MARK KRITZMAN, AND DAVID TURKINGTON

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Will Kinlaw, Mark Kritzman, and David Turkington

Will Kinlaw
is a senior managing director at State Street Global Markets in Cambridge, MA.
wbkinlaw@statestreet.com

Mark Kritzman
is the president and CEO of Windham Capital Management, LLC, in Boston, MA.
mkritzman@windhamcapital.com

David Turkington
is a managing director at State Street Global Markets in Cambridge, MA.
dturkington@statestreet.com

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 the 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; see, for example, Billio et al. [2010] and Haldane [2009]. It is notoriously difficult, if not impossible, however, 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.

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.

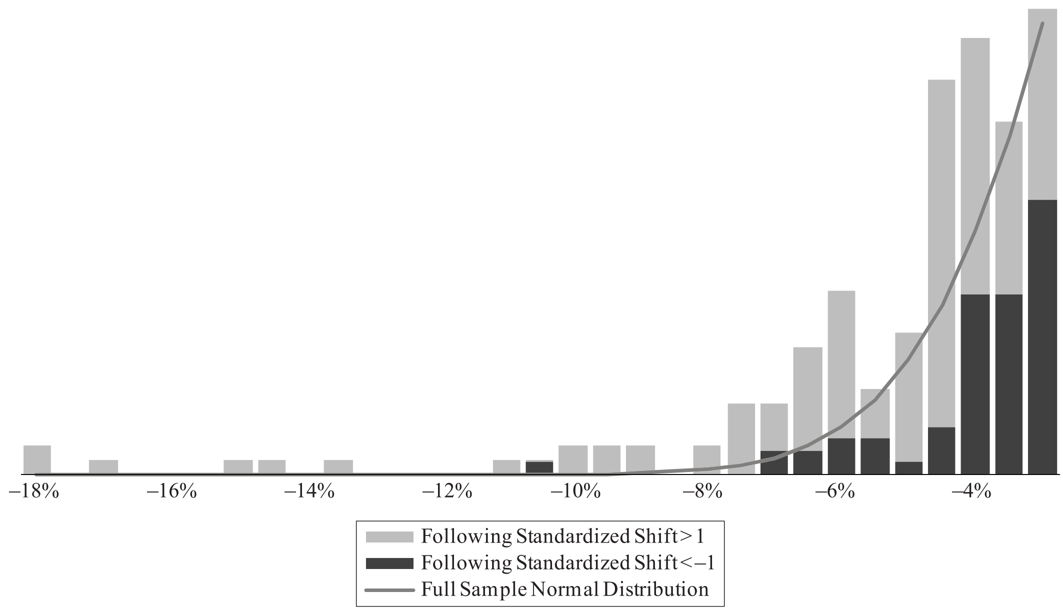
THE ABSORPTION RATIO AS A MEASURE OF SYSTEMIC RISK

The absorption ratio, introduced by Kritzman et al. [2011], 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),

$$AR = \frac{\Sigma_{i=1}^{n}\sigma_{Ei}^{2}}{\Sigma_{j=1}^{N}\sigma_{Aj}^{2}} \qquad (1)$$

EXHIBIT 1

Realized Left Tail of One-Week U.S. Equity Returns Following High and Low Systemic Risk



Note: Approximately 10% of the full sample empirical distribution lies below –3%.

where

AR = absorption ratio
N = number of assets
n = number of eigenvectors in numerator of absorption ratio
σ^2_{Ei} = variance of the i^{th} eigenvector
σ^2_{Aj} = variance of the j^{th} asset

Kritzman et al. [2011] provided 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.[1]

Throughout our research, we use the same parameters as Kritzman et al. [2011] 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% of the number of assets in our universe. Kritzman et al. showed 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) as follows:

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

where

ΔAR = standardized shift in the absorption ratio
$AR_{15\ \text{Day}}$ = 15-day moving average of the absorption ratio
$AR_{1\ \text{Year}}$ = one-year moving average of the absorption ratio
σ = standard deviation of the absorption ratio over the one-year period

The absorption ratio may be interpreted as a measure of market fragility. Kritzman et al. [2011] showed 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 that was greater than one. The authors are quick to point out that fragility by itself is not sufficient to cause market losses, but 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 that links the MSCI U.S. industry absorption ratio to the probability of large losses in the aggregate MSCI U.S. index. Exhibit 1 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 U.S. equity returns from January 1998 through June 2011.

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 that takes into account three features:

1. It captures the asset's vulnerability to failure.[2]
2. It captures how broadly and deeply an asset is connected to other assets in the system.[3]
3. It captures the riskiness of the other assets to which it is connected.

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 compose 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 composing the subset of the most important ones. This gives a measure of centrality, which is defined in Equation (3).

$$CS_i = \frac{\sum_{j=1}^{n}\left(AR^j \cdot \frac{|EV_i^j|}{\sum_{k=1}^{N}|EV_k^j|}\right)}{\sum_{j=1}^{n} AR^j} \tag{3}$$

where

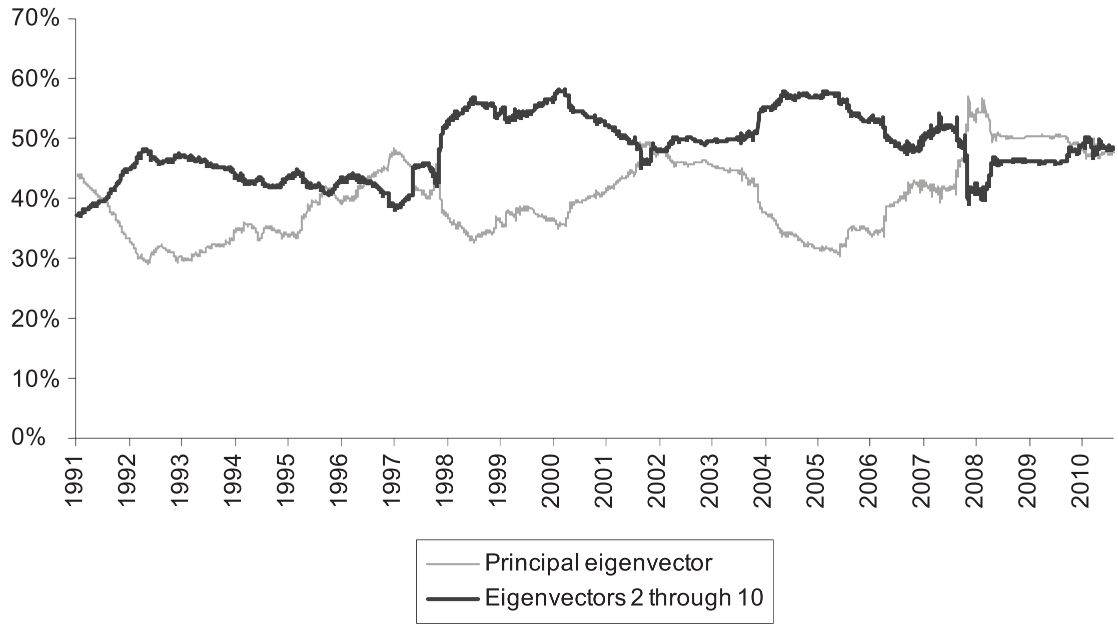
CS_i = asset centrality score
AR^j = absorption ratio of the j^{th} eigenvector
EV_i^j = absolute value of the exposure of the i^{th} asset within the j^{th} eigenvector
n = number of eigenvectors in the numerator of the absorption ratio
N = total number of assets

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 nonlinear.[4]

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), the score would equal precisely the weight of the asset in the first eigenvector.[5] We instead use several eigenvectors in the numerator of the absorption

EXHIBIT 2

Explanatory Power of the Top Eigenvectors (absorption ratio of U.S. financials 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 REIT industry within the financial 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.

ratio because most of the time several factors contribute importantly to market variance. For example, Exhibit 2 shows the explanatory power of the principal eigenvector compared to the collective explanatory power of the second through the tenth eigenvectors.

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. We are not interested, however, 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 both the U.S. and global financial sectors.

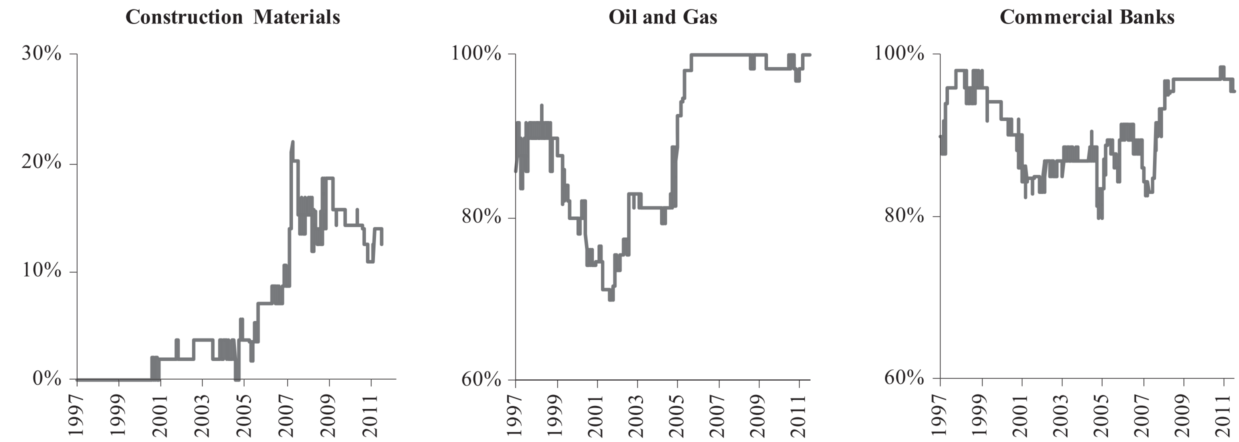
RESULTS

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

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

Exhibit 3

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.

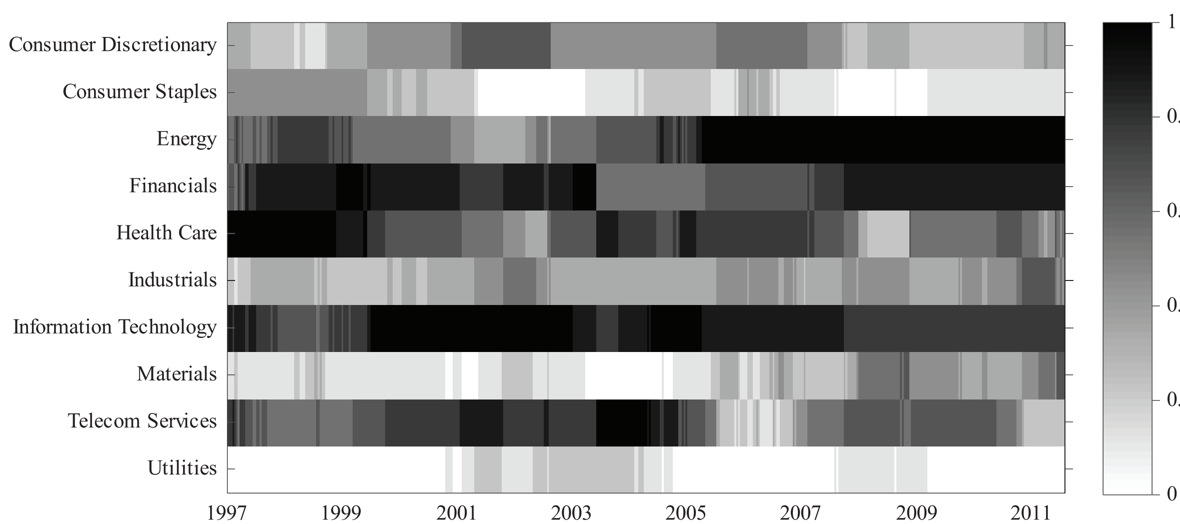
of the late 1990s and the more recent global financial crisis.

Exhibit 4 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 turmoil within these sectors.

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

Exhibit 4

U.S. Sector Centrality Percentile Ranks



Notes: We aggregate the MSCI U.S. GICS Level 3 industry centrality scores by the square root of their market capitalization to obtain 10 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 10 sectors.

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.[6]

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

Exhibit 6 shows the 10 most systemically important U.S. industries. Exhibit 6 reveals, not surprisingly, that the most systemically important industries reside primarily 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 7 shows the 10 most systemically important U.S. financial companies.[7]

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 7 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 8.

Exhibit 9 offers further evidence that Lehman Brothers' centrality and systemic importance increased leading up to and throughout the global financial crisis.

EXHIBIT 5
Sector Systemic Importance (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 6
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

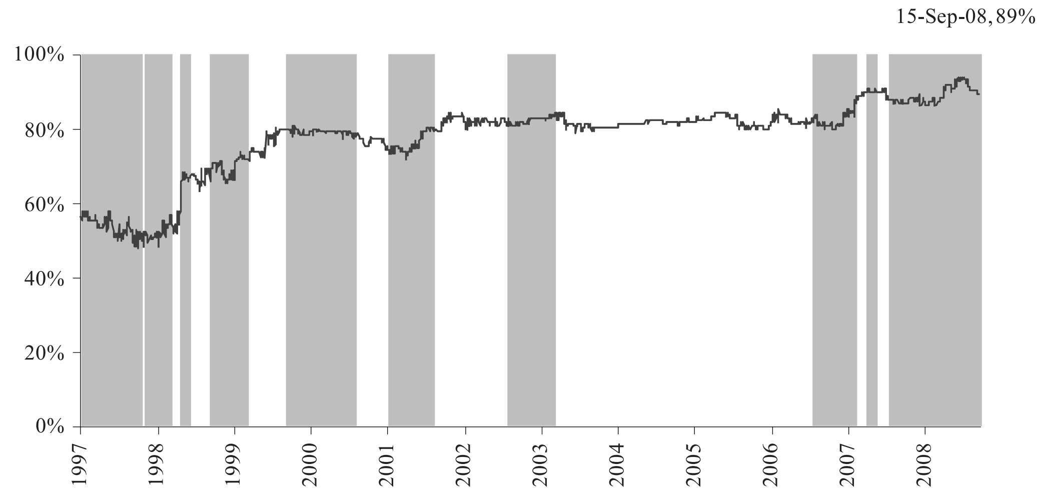
Notes: Averages are computed over the time period for which data were available for each industry.

EXHIBIT 7
Top 10 Systemically Important U.S. Financial Stocks (December 1992–June 2011)

Top U.S. Financial Stocks When Standardized 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

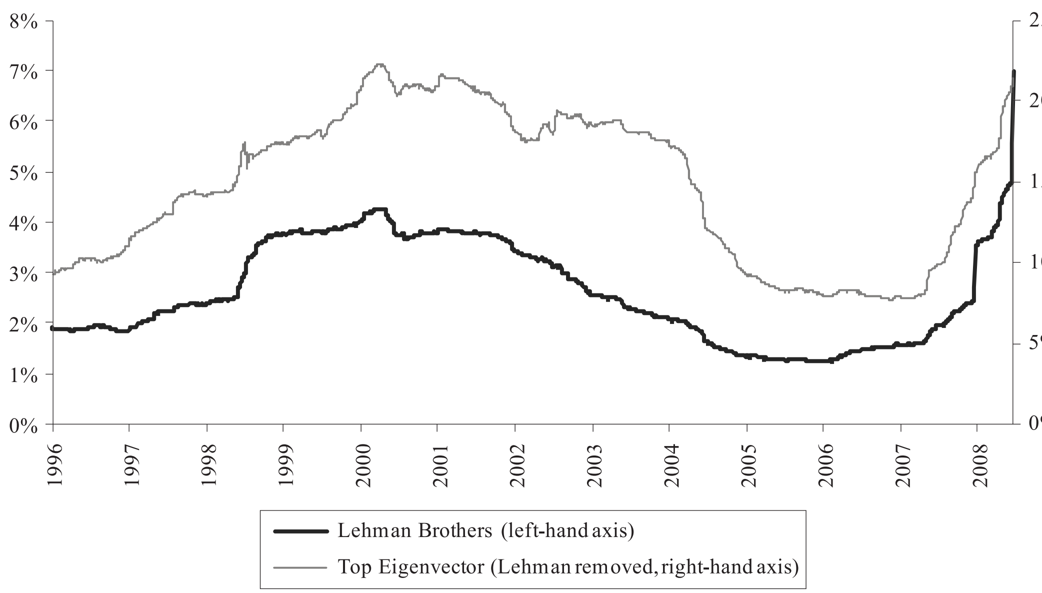
Notes: Averages are computed over the time period for which data were available for each company.

EXHIBIT 8
Lehman Brothers Centrality Score Through Time



Notes: Shading represents high systemic risk within the financial sector, which we define as a standardized shift of the absorption ratio that is greater than one.

EXHIBIT 9
Daily Volatility Over the Preceding Two Years



Notes: Both the eigenvector volatility and the Lehman Brothers volatility are computed using the same parameters as before, including the 500-day rolling window with exponential weighting.

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.

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.[8] In this setting, we use locally denominated returns to avoid introducing currency-related distortions. We also use

Exhibit 10

Comparison of Our Methodology to the Financial Stability Board Methodology

	Our Methodology	Financial Stability Board
Data and Calculation	Systemic importance scores are derived from security price movements by 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%)
Timeline	One-week delay	Two-year delay**

** See Basel Committee on Banking Supervision [2011].*

*** See Financial Stability Board [2011].*

Exhibit 11

Top 29 Systemically Important Global Financial Institutions Excluding Insurance Companies and Other Nonbank Financial Institutions as of December 25, 2009

Rank	Global Financial Institutions		
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	U.S. Bancorp	28	State Street
14	UBS	29	Standard Chartered
15	ING		

= also appears on the FSB list of 29 systematically important financial institutions.

Exhibit 12

Top 25 Systemically Important Global Financial Institutions as of November 25, 2011

Rank	Global Financial Stocks	Rank	Global Financial Stocks
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	U.S. Bancorp
13	Morgan Stanley		

weekly returns to mitigate the problem of asynchronous market close times across time zones.[9]

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.

The global Financial Stability Board (FSB) [2011] named 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." The FSB uses a detailed methodology designed by the Basel Committee on Banking Supervision [2011], which involves aggregating each institution's scores across 12 fundamental indicators. Exhibit 10 highlights the differences between our methodology and the FSB methodology.

Exhibit 11 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 nonbank financial institutions in order to facilitate comparison with the FSB list.

Exhibit 13

Stratification of the Top 25 Systemically Important Global Financial Institutions Compared to the Full Universe of Institutions as of November 25, 2011

Country	Top 25 (%)	All (%)
Australia	0	5
Austria	0	1
Belgium	0	2
Canada	0	8
Denmark	0	1
Finland	0	1
France	16	4
Germany	8	2
Greece	0	2
Hong Kong	0	2
Israel	0	2
Italy	8	4
Japan	0	14
Netherlands	4	1
Norway	0	0
Portugal	0	1
Singapore	0	2
Spain	8	3
Sweden	0	4
Switzerland	8	4
United Kingdom	16	8
United States	32	31

Region	Top 25 (%)	All (%)
Asia Pacific	0	23
Europe	68	38
North America	32	39
MSCI GICS Industry		
Insurance	12	31
Diversified Financial Services	16	11
Commercial Banks	52	41
Consumer Finance	0	2
Capital Markets	20	14
Thrifts & Mortgage Finance	0	1
Market Capitalization		
50 billion USD or larger	28	8
10–50 billion USD	72	36
5–10 billion USD	0	21
1–5 billion USD	0	33
1 billion USD or smaller	0	2

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%) 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 11 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 12 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 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 13 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 in 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.

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 November 25, 2011

1 Bank of America	18 BBV Argentaria	35 Sumitomo Mitsui FG	52 Prudential
2 Citigroup	19 UBS	36 Berkshire Hathaway	53 Franklin Resources
3 JP Morgan Chase	20 Credit Suisse	37 Westpac	54 Swiss Re
4 Wells Fargo	21 Credit Agricole	38 Nordea	55 Mizuho FG
5 BNP Paribas	22 Deutsche Bank	39 State Street	56 Dexia
6 Santander	23 Allianz	40 Capital One	57 ANZ Banking Group
7 Lloyds Banking Group	24 Met Life	41 Hartford Financial	58 Natixis
8 Barclays	25 US Bancorp	42 Aflac	59 Aegon
9 HSBC	26 AIG	43 Royal Bank of Canada	60 Lincoln National
10 Royal Bank of Scotland	27 Mitsubishi UFJ FG	44 Aviva	61 Ageas
11 Societe Generale	28 American Express	45 Suntrust	62 Blackrock
12 Unicredit	29 Prudential Financial	46 National Australia Bank	63 Fifth Third Bancorp
13 Morgan Stanley	30 KBC Groupe	47 Commonwealth Bk of Australia	64 National Bank of Greece
14 Goldman Sachs	31 PNC Group	48 Zurich Financial	65 Regions Financial
15 ING	32 Standard Chartered	49 Erste Group	66 Toronto-Dominion Bank
16 AXA	33 Bank of New York Mellon	50 Assicurazioni Generali	67 BB&T
17 Intesa Sanpaolo	34 Manulife Financial	51 Commerzbank	68 Hong Kong Exch. & Clearing

Exhibit A1 *(continued)*

69 Tokio Marine
70 Danske Bank
71 Nomura
72 SEB
73 BOC Hong Kong
74 Bank of Nova Scotia
75 Meunchener Ruck.
76 Principal Financial
77 Charles Schwab
78 DNB NOR
79 Raiffeisen Bank
80 CME Group
81 Great West Life
82 T Rowe Price
83 Swedbank
84 Sun Life
85 Keycorp
86 Genworth Financial
87 Allstate
88 Legal & General
89 Hang Seng Bank
90 Travelers
91 Ameriprise
92 Banco Popular Espanol
93 Canadian Imperial Bank
94 Orix
95 QBE Insurance Group
96 ACE
97 NYSE Euronext
98 Svenska Handelsbanken
99 Bank of Montreal
100 Leucadia National
101 Macquarie
102 MS&AD Insurance Group
103 Sampo
104 Man Group
105 SLM
106 Northern Trust
107 EFG Eurobank Ergasias
108 Loews
109 Banco Popolare
110 Banca Monte dei Paschi
111 CNP Assurances
112 TD Ameritrade
113 Old Mutual
114 Mapfre
115 XL Group
116 Resona Holdings
117 Power Financial
118 M&T Bank
119 Chubb
120 Alpha Bank
121 DBS Group
122 Moody's
123 T&D Holdings
124 Comerica
125 Mediobanca
126 UBI Banca
127 United Overseas Bank
128 Standard Life
129 Unum
130 Intercontinental
131 AMP
132 Legg Mason
133 Sumitomo Mitsui Trust
134 OCBC
135 Groupe Bruxelles Lambert
136 GAM
137 Bank of Cyprus
138 Daiwa Securities
139 Marsh & McLennan
140 Vienna Insurance
141 Progressive
142 Power Corp of Canada
143 Banco Sabadell
144 Nasdaq OMX
145 Banco Espirito Santo
146 Jefferies
147 Swiss Life
148 ICAP
149 Pargesa
150 Suncorp
151 Intesa Sanpaolo RNC
152 Schroders
153 BCP Banco Comercial 210 ASX
154 Investor
155 AON
156 Eaton Vance
157 Bankinter
158 Eurazeo
159 Bank East Asia
160 Hudson City Bancorp
161 3i Group
162 Torchmark
163 Hannover Ruck.
164 London Stock Exchange
165 National Bank of Canada
166 New York Community Bancorp
167 Bank of Yokohama
168 Assurant
169 Credit Saison
170 SEI Investments
171 Pohjola bank
172 Shinsei Bank
173 Banca Carige
174 Leumi
175 Axis Capital
176 Investec
177 Singapore Exchange
178 Chiba Bank
179 Baloise
180 IGM Financial
181 SBI
182 Royal & Sun Alliance
183 Bank Hapoalim
184 Fidelity National Financial
185 Old Republic International
186 Cincinnati Financial
187 Ratos
188 Peoples United
189 Kinnevik
190 Shizuoka Bank
191 Mitsubishi UFJ Lease & Fin
192 Admiral Group
193 SCOR
194 Fukuoka FG
195 Wing Hang Bank
196 Willis Group
197 Insurance Australia Group
198 Bendigo & Adelaide Bank
199 Partnerre
200 Industrial Alliance
201 Onex
202 CI Financial
203 Hokuhoku FG
204 W. R. Berkley
205 Joyo Bank
206 Everest Real Estate
207 Arch Capital
208 Industrivarden
209 Aeon Credit Service
211 Bank Kyoto
212 Suruga Bank
213 Yamaguchi FG
214 Hachijuni Bank
215 Nishi-Nippon City Bank
216 Aozora Bank
217 Israel Discount Bank
218 Mizrahi Tefahot Bank
219 Chugoku Bank
220 Gunma Bank
221 Hiroshima Bank
222 RenaissanceRe
223 TrygVesta
224 Intact Financial
225 IYO Bank
226 TMX Group
227 Fairfax

ENDNOTES

The views expressed in this article are the views solely of the authors and do not necessarily represent the views of, and should not be attributed to, MIT Sloan School, State Street Corporation, or Windham Capital Management.

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

[2]We use volatility as a proxy for vulnerability to failure.

[3]By broad, we mean the number of assets to which it is correlated, and by deep, we mean the strength of its correlations.

[4]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 produce 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.

[5]For additional discussion of eigenvector centrality, see Bonacich [1972].

[6]Sector centrality scores are computed as the square root 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 10 broad sector indices.

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

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

[9]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% 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 reconstituting 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.

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