Principal Components as a Measure of Systemic Risk

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The U. S. government's failure to provide oversight and prudent regulation of the financial markets, together with excessive risk taking by some financial institutions, pushed the world financial system to the brink of systemic failure in 2008. As a consequence of this near catastrophe, both regulators and investors have become keenly interested in developing tools for monitoring systemic risk. But this is easier said than done. Securitization, private transacting, and "flexible" accounting[5] prevent us from directly observing the many explicit linkages of financial institutions. As an alternative, we introduce a measure of implied systemic risk called the absorption ratio, which equals the fraction of the total variance of a set of asset returns explained or "absorbed" by a fixed number of eigenvectors. The absorption ratio captures the

[1] Windham Capital Management, LLC and MIT, Sloan School
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[3] State Street Associates
[4] MIT, Sloan School and NBER
[5] Euphemism for accounting practices such as Lehman Brothers' use of swaps to conceal $50 billion of debt shortly before its demise.

extent to which markets are unified or tightly coupled. When markets are tightly coupled, they become more fragile in the sense that negative shocks propagate more quickly and broadly than when markets are loosely linked.

We offer persuasive evidence that the absorption ratio effectively captures market fragility. We show that:

1. Most significant U.S. stock market drawdowns were preceded by spikes in the absorption ratio.

2. Stock prices, on average, depreciated significantly following spikes in the absorption ratio and, on average, appreciated significantly in the wake of sharp declines in the absorption ratio.

3. The absorption ratio was a leading indicator of the U.S. housing market bubble.

4. The absorption ratio systematically rose in advance of market turbulence.

5. Shifts in the absorption ratio coincided with major global financial crises and tracked changes in independent measures of contagion.

We proceed as follows. In Part I we provide a literature review of systemic risk and related topics. In Part II we provide a formal description of the absorption ratio. In Part III we present historical estimates of the absorption ratio for a variety of asset markets, and we show how it relates to asset prices, financial turbulence, and the global financial crisis. We summarize in Part IV and suggest how regulators and investors might use the absorption ratio as an early warning signal of market stress.

Part I: Literature Review

De Bandt and Hartmann (2000) provide an extensive review of the literature on systemic risk. Most studies in this review focus on contagion and "financial fragility," and the literature on contagion itself is quite rich (see, for example, Rigobon, 2001 and Rigobon, 2006). Recently, the IMF included a chapter on detecting systemic risk in its Global Financial Stability Report (2009), which stated, "The current crisis demonstrates the need for tools to detect systemic risk," as well as, "Being able to identify systemic events at an early stage enhances policymakers' ability to take necessary exceptional steps to contain the crisis." As a simple starting point, the IMF report suggests monitoring conditional (stress) correlations.

In a related study, Billio, Getmansky, Lo, and Pelizzon (2010) show that correlations increase during market crashes. Prior studies have shown that exposure to different country equity markets offers less diversification in down markets than in up markets.[6] The same is true for global industry returns (Ferreira and Gama, 2004), individual stock returns (Ang, Chen, and Xing, 2002, Ang and Chen, 2002, and Hong, Tu, and Zhou. 2003), hedge fund returns (Van Royen, 2002a), and international bond market returns (Cappiello, Engle, and Sheppard, 2006).

Both the IMF's Global Financial Stability Report (2009) and Billio, Getmansky, Lo, and Pelizzon (2010) suggest that an important symptom of systemic risk is the presence of sudden regime shifts. Investors have long recognized that economic conditions frequently undergo abrupt changes. The economy typically oscillates between

-a steady, low volatility state characterized by economic growth; and

[6] See, for example, Ang and Bekaert, 2002, Kritzman, Lowry, and Van Royen, 2001, and Baele, 2003, on regime shifts; Van Royen, 2002b, and Hyde, Bredin, and Nguyen, 2007 on financial contagion; and Longin and Solnik, 2001, Butler and Joaquin, 2001, Campbell, Koedijk, and Kofman, 2002, Cappiello, Engle, and Sheppard, 2006, and Hyde, Bredin, and Nugyen, 2007 on correlation asymmetries.

-a panic-driven, high volatility state characterized by economic contraction.

Evidence of such regimes has been documented in short-term interest rates (Gray, 1996, Ang and Bekaert, 2002, Smith, 2002), GDP or GNP (Hamilton, 1989, Goodwin, 1993, Luginbuhl and de Vos, 1999, Lam, 2004), inflation Kim, 1993, Kumar and Okimoto, 2007), and market turbulence (Chow, Jacquier, Kritzman, and Lowry, 1999, Kritzman, Lowry, and Van Royen, 2001, and Kritzman and Li, 2010).

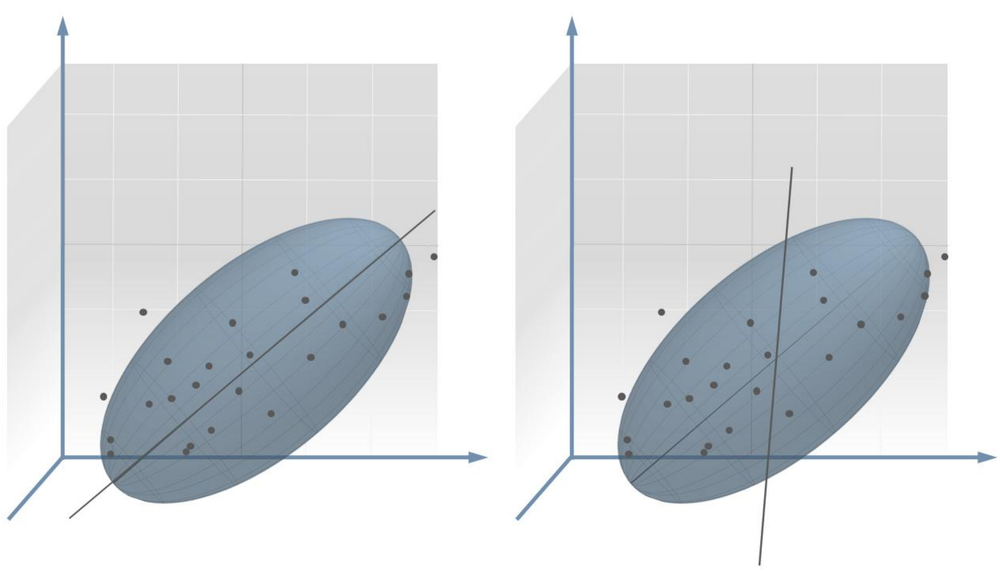
Billio, Getmansky, Lo, and Pelizzon (2010) independently applied principal components analysis to determine the extent to which several financial industries became more unified across two separate regimes. They found that the percentage of the total variance of these industries explained by a single factor increased from 77% during the 1994-2000 period to 83% during the 2001-2008 period. We instead apply principal components analysis to several broad markets and estimate the fraction of total market variance explained by a finite number of factors on a rolling basis throughout history. We call this measure the absorption ratio. We also introduce a standardized measure of shifts in the absorption ratio, and we analyze how these shifts relate to changes in asset prices and financial turbulence. By applying a moving window in our estimation process, we account for potential changes in the risk factors over time. Because Lo, et al. divide history into only two periods, they assume implicitly that these periods are distinct regimes and are stationary within themselves.

Part II: The Absorption Ratio

Consider a covariance matrix of asset returns estimated over a particular time period. The first eigenvector is a linear combination of asset weights that explains the greatest fraction of the assets' total variance. The second eigenvector is a linear combination of asset weights orthogonal to the first eigenvector that explains the greatest fraction of leftover asset variance; that is, variance not yet been explained or absorbed by the first eigenvector. The third eigenvector and beyond are identified the same way. They absorb the greatest fraction of leftover variance and are orthogonal to preceding eigenvectors.

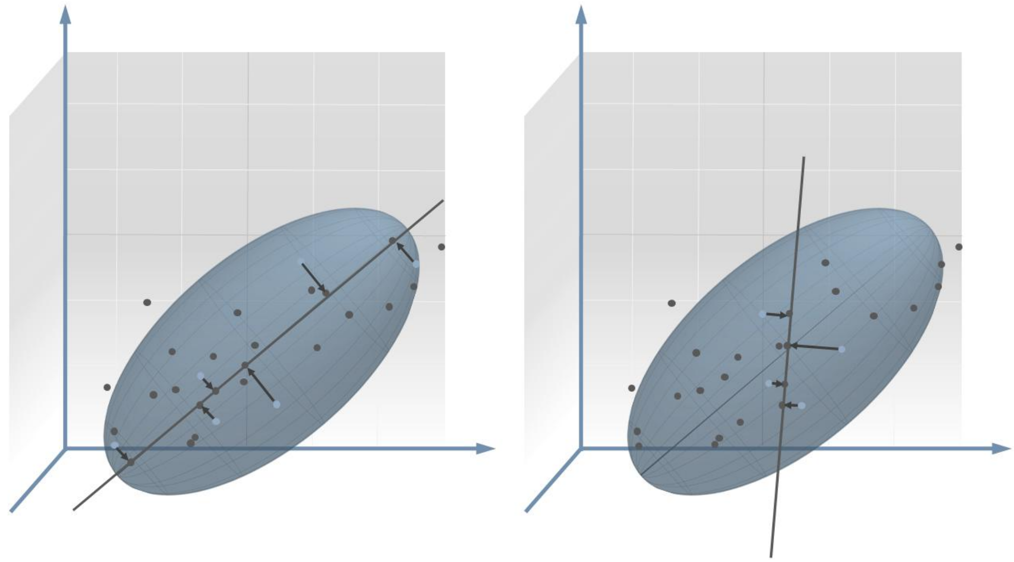
It is perhaps more intuitive to visualize eigenvectors. The left panel of Figure 1 shows a three-dimensional scatter plot of asset returns with a vector piercing the observations. Each observation is the intersection of returns of three assets for a given period, which might be a day, a month, or a year, for example. This vector represents a linear combination of the assets and is a potential eigenvector. The right panel of Figure 1 shows the same scatter plot of asset returns but with a different vector piercing the observations.

Exhibit 1: Three Dimensional Scatter Plots of Asset Returns



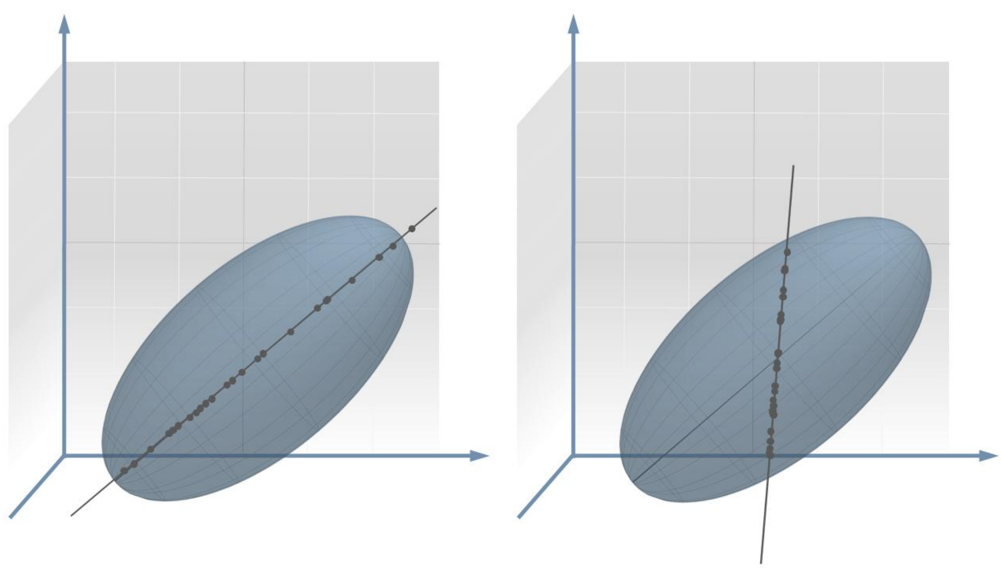
Of all the potential vectors piercing this scatter plot, we determine the first eigenvector by perpendicularly projecting the observations onto each potential eigenvector.

Exhibit 2: Projection of Observations onto Vectors



The first eigenvector is the one with the greatest variance of the projected observations, as shown in Figure 2.[7]

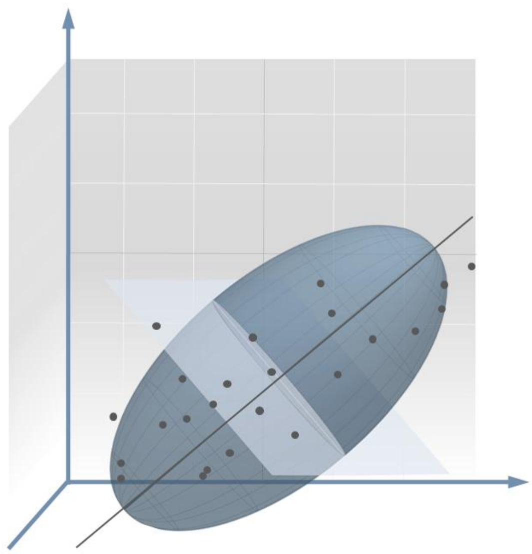
Exhibit 3: First Eigenvector



[7]There are a variety of techniques to identify eigenvectors. We can use matrix algebra to identify eigenvectors given a small set of observations. For larger data sets, it is more efficient to resort to numerical procedures.

In order to identify the second eigenvector, we first consider a plane passing through the scatter plot that is orthogonal to the first eigenvector.

Exhibit 4: Second Eigenvector



The second eigenvector must lie on this orthogonal plane, thereby limiting our search. It is the vector that yields the second highest variance of projected observations. We find the third eigenvector in the same fashion. It is the vector that yields the third greatest variance and is orthogonal to the first two vectors. These three eigenvectors together explain the total variance of the assets.[8]

We may or may not be able to associate these eigenvectors with observable economic or financial variables. In some cases the asset weights of the eigenvector may suggest an obvious factor. For example, if we were to observe short exposures to the airline industry and other

[8] The number of eigenvectors never exceeds the number of assets; however, total variation could be explained by fewer eigenvectors than assets to the extent assets are redundant. To be precise, the total number of eigenvectors equals the rank of the covariance matrix.

industries that consume fuel and long exposures to the oil industry and other industries that profit from rising oil prices, we might conclude that this eigenvector is a proxy for the price of energy. Alternatively, an eigenvector may reflect a combination of several influences that came together in a particular way unique to the chosen sample of assets, in which case the factor may not be definable other than as a statistical artifact. Moreover, the composition of eigenvectors may not persist through time. The sources of risk may change from period to period.

In some applications this artificiality or non-stationarity would be problematic. If our intent were to construct portfolios that were sensitive to a particular source of risk, then we would like to be able to identify it and have some confidence of its persistence as an important risk factor. But here our interest is not to interpret sources of risk; rather we seek to measure the extent to which sources of risk are becoming more or less compact.

The particular measure we use as an indicator of systemic risk is the absorption ratio, which we define as the fraction of the total variance of a set of assets explained or absorbed by a finite set of eigenvectors, as shown.

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

where,

AR: Absorption Ratio

N: number of assets

n: number of eigenvectors used to calculate AR

σ_{Ei}^2: variance of the i-th eigenvector, sometimes called eigenportfolio

σ_{Aj}^2: variance of the j-th asset

A high value for the absorption ratio corresponds to a high level of systemic risk, because it implies the sources of risk are more unified. A low absorption ratio indicates less systemic risk, because it implies the sources of risk are more disparate. It is important to keep in mind, though, that high systemic risk does not necessarily lead to asset depreciation or financial turbulence. It is simply an indication of market fragility in the sense that a shock is more likely to propagate quickly and broadly when sources of risk are tightly coupled.

Part III: Empirical Analysis the Absorption Ratio

The Absorption Ratio and Stock Returns

In order to estimate the absorption ratio, we use a window of 500 days to estimate the covariance matrix and eigenvectors, and we fix the number of eigenvectors at approximately 1/5th the number of assets in our sample.[9] Exhibit 5 shows a time series of the absorption ratio estimated from the returns of the 51 U.S. industries (hence 10 eigenvectors) in the MSCI USA index based on trailing 500 day overlapping windows, along with the level of MSCI USA price index from January 1, 1998 through January 31, 2010.

[9] In principle, we should condition the number of eigenvectors on the rank of the covariance. Our approach does this to the extent the assets are independent.

Exhibit 5: Absorption Ratio and U.S. Stock Prices

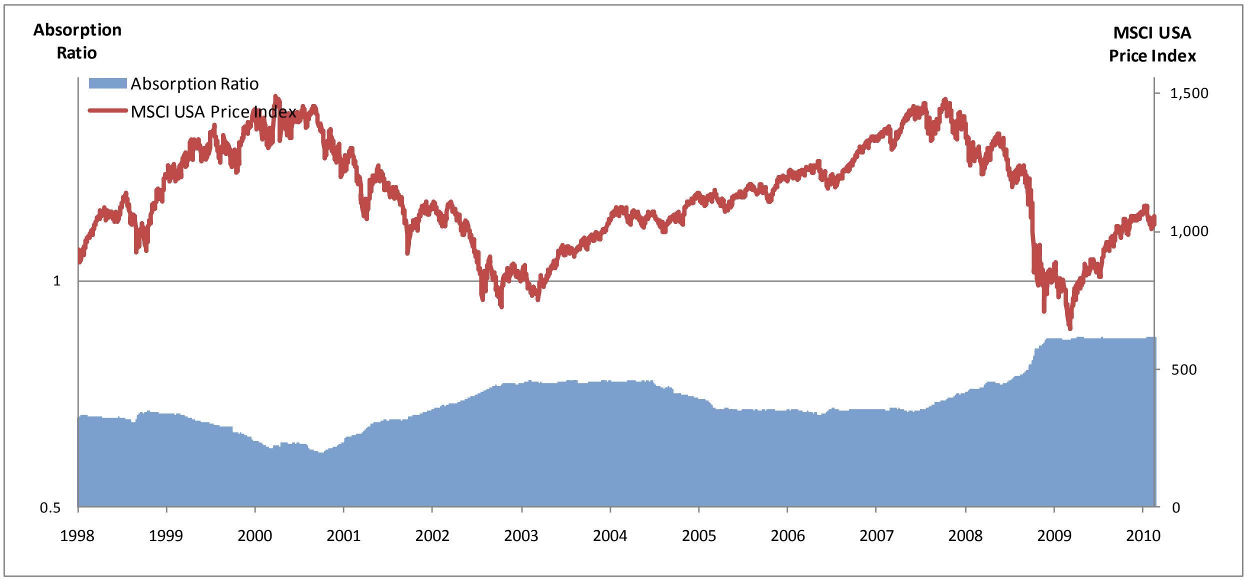


Exhibit 5 shows a distinct inverse association between the level of the absorption ratio and the level of U.S. stock prices. It also reveals that the absorption ratio increased sharply to its highest level ever during the global financial crisis of 2008, coincident with a steep decline in stock prices, and that although stock prices have partially recovered as of the first quarter of 2010, the absorption ratio remains at its historic peak. This continued high level for the absorption ratio, while perhaps worrisome, does not necessarily foretell a renewed selloff in stocks. It does suggest, however, that the U.S. stock market remains extremely fragile and therefore highly vulnerable to negative shocks.

A casual review of absorption ratio along side stock prices suggests a coincident relationship, which invites the question of whether or not the absorption ratio might be useful as a signal of impending trouble. Exhibit 6 sheds some light on this question. It shows the fraction of significant drawdowns preceded by a spike in the absorption ratio.

Exhibit 6: Absorption Ratio and Drawdowns

Fraction of drawdowns preceded by spike in AR			
	1% worst	2% worst	5% worst
1 Day	87.50%	84.13%	73.42%
1 Week	81.25%	80.95%	76.58%
1 Month	100.00%	98.41%	89.81%
1 standard deviation, 15 days / 1 year 1/1/1998 through 1/31/2010			

We first compute the moving average of the absorption ratio over 15 days and subtract it from the moving average of the absorption over one year. We then divide this difference by the standard deviation of the one-year absorption ratio. Exhibit 6 reports the fraction of significant drawdowns that were preceded by a one-standard deviation spike in the 15-day absorption ratio relative to the one-year absorption ratio. For example, all of the 1% worst monthly drawdowns were preceded by a one-standard deviation spike in the absorption ratio. And a very high percentage of other significant drawdowns occurred after the absorption ratio spiked.

We should not conclude from this exhibit that a spike in the absorption ratio reliably leads to a significant drawdown in stock prices. In many instances, stocks performed well following a spike in the absorption ratio. We would be correct to conclude, though, that a spike in the absorption ratio is a near necessary condition for a significant drawdown, just not a sufficient condition. Again, a high absorption ratio is an indication of market fragility.

Even though a spike in the absorption ratio does not always lead to a major drawdown in stock prices, stocks, on average, perform much worse following spikes in the absorption ratio than they do in the wake of a sharp drop in the absorption ratio. Exhibit 7 shows the average annualized one-day, one-week, and one-month returns following a one-standard deviation increase or decrease in the 15-day absorption ratio relative to the one-year absorption ratio.

Exhibit 7: Absorption Ratio and Subsequent Returns

Annualized return after extreme AR			
	1 Sigma Increase	1 Sigma Decrease	Difference
1 Day	-4.50%	5.96%	-10.46%
1 Week	-4.16%	4.39%	-8.55%
1 Month	-2.81%	3.31%	-6.12%
1 standard deviation change, 15 days / 1 year 1/1/1998 through 1/31/2010			

Exhibit 7 offers compelling evidence that significant increases in the absorption ratio are followed by significant stock market losses on average, while significant decreases in the absorption ration are followed by significant gains. This differential performance suggests that it might be profitable to reduce stock exposure subsequent to an increase in the absorption ratio and to raise exposure to stocks after the absorption ratio falls, which is what we next test.

Exhibit 8 shows the performance of a dynamic trading strategy in which the stock exposure of an otherwise equally weighted portfolio of stocks and government bonds is raised to 100% following a one-standard deviation decrease in the 15-day absorption ratio relative to the one-year absorption ratio and reduced to 0% following a one-standard deviation increase. These rules are summarized below.

Absorption Ratio	Stocks/Bonds
$- 1\sigma \geq$ AR $\leq + 1\sigma$	50/50
AR > + 1σ	0/100
AR < - 1σ	100/0

These rules are applied daily with a one-day lag following the signal for the period January 1, 1998 through January 31, 2010 using the MSCI USA stock index and Treasury bonds.[10] Exhibit 8 shows that these rules triggered only 2.56 trades per year on average, which should not be surprising given that one-standard deviation events occur infrequently. Nonetheless, these infrequent shifts improved return by more than 3% annually while lowering risk by 0.45%, thereby raising the return/risk ratio from 0.44 to 0.75.

Exhibit 8: Absorption Ratio as a Market Timing Signal

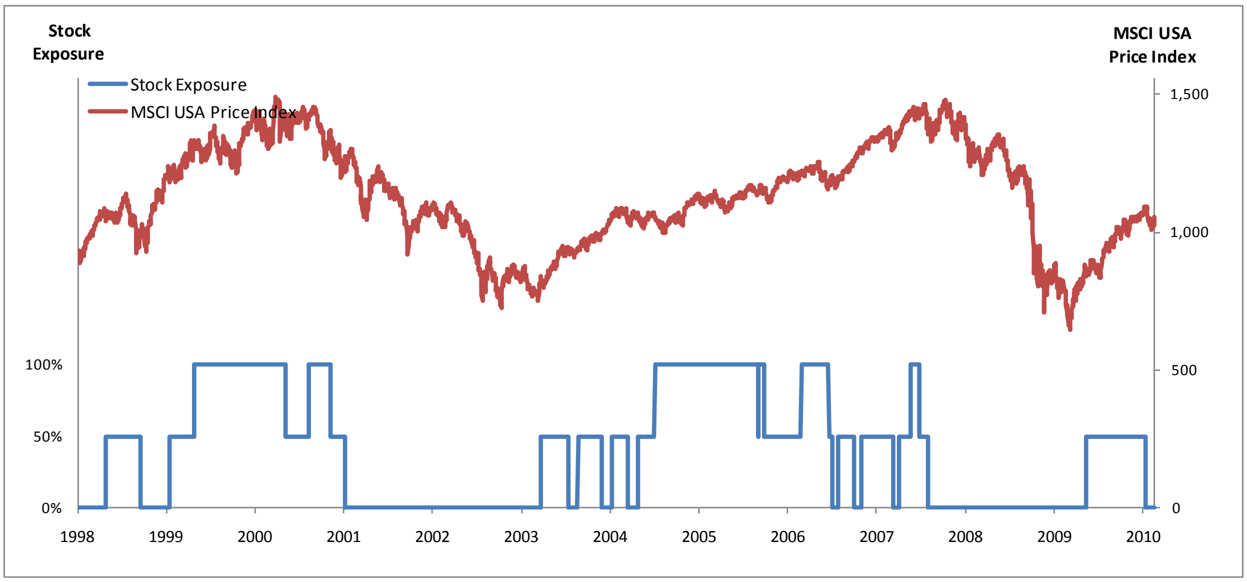
Performance: 100/0 versus 0/100 (1-day implementation lag)		
	Dynamic	50/50
Return	7.82%	4.79%
Risk	10.47%	10.92%
Return/Risk	0.75	0.44
Turnover		127.92%
Number of trades		2.56
1/1/1998 through 1/31/2010		

Although most investors might be reluctant to shift entirely in or out of stocks given a single signal, this experiment does offer persuasive evidence of the potential value of the

[10] We also require about two years to estimate the covariance matrix and eigenvectors and another year to estimate the standard deviation of the one-year moving average; hence our data begins January 1, 1995.

absorption ratio as a market timing signal.[11] Exhibit 9 reveals that the absorption ratio would have kept investors out of stocks during much of the dot com meltdown as well as the global financial crisis. It also reveals that the absorption ratio produced some false positives, but not enough to offset its net beneficial effect.

Exhibit 9: Absorption Ratio Stock Exposure



This trading rule appears to improve performance in other the stock markets as well. Exhibits 10 and 11 show that that the absorption ratio estimated from stock returns in Canada, Germany, Japan, and the U.K. and applied as a timing signal in those markets yielded similar improvement in total return as well as risk-adjusted return.[12]

[11] Perhaps a less extreme strategy would be to maintain a 50/50 stock/bond mix and to purchase call options on stocks when the absorption ratio fell sharply and put options when it spiked.
[12] As with the U.S. stock market, we set the number of eigenvectors at about 1/5th the number of industries.

Exhibit 10: Global Performance of Absorption Ratio

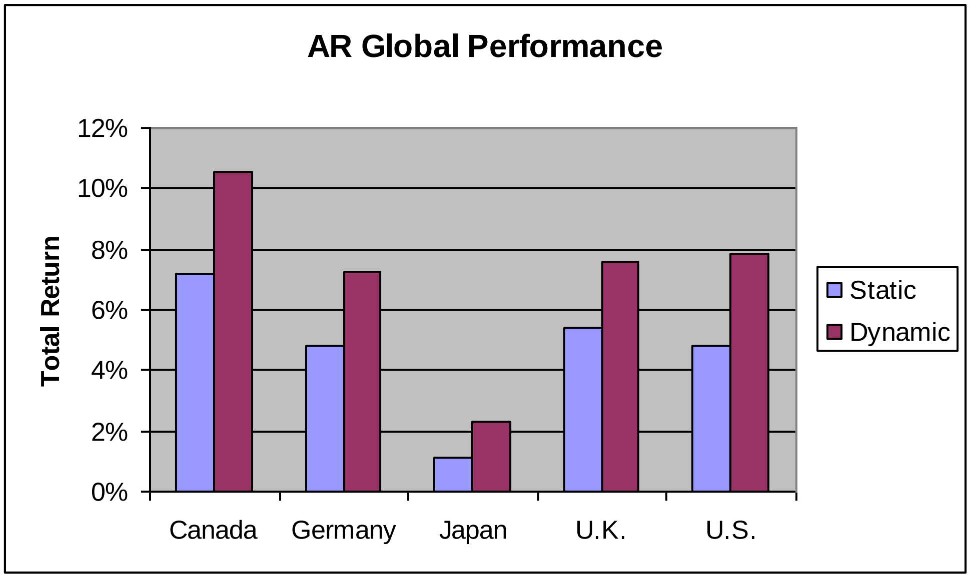
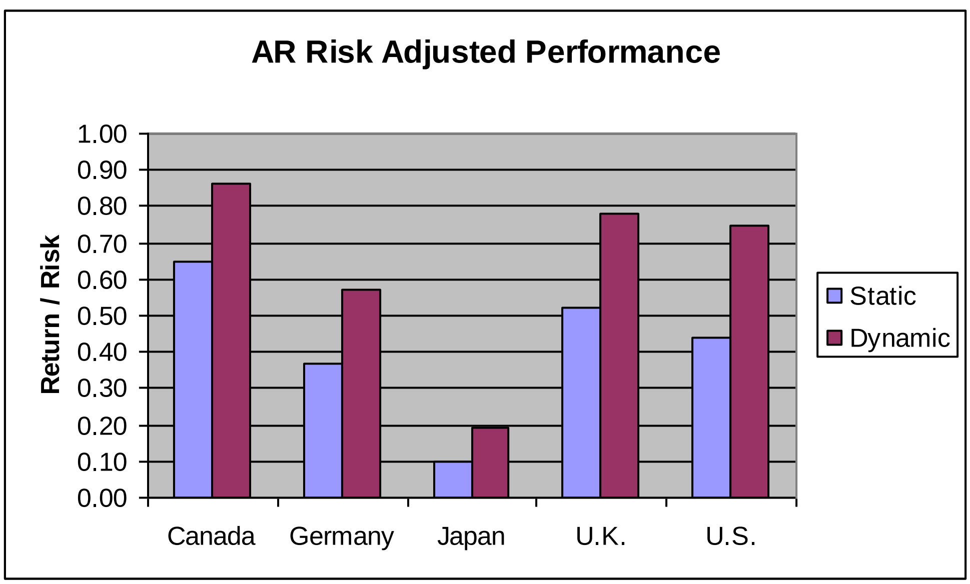


Exhibit 11: Global Performance of Absorption Ratio

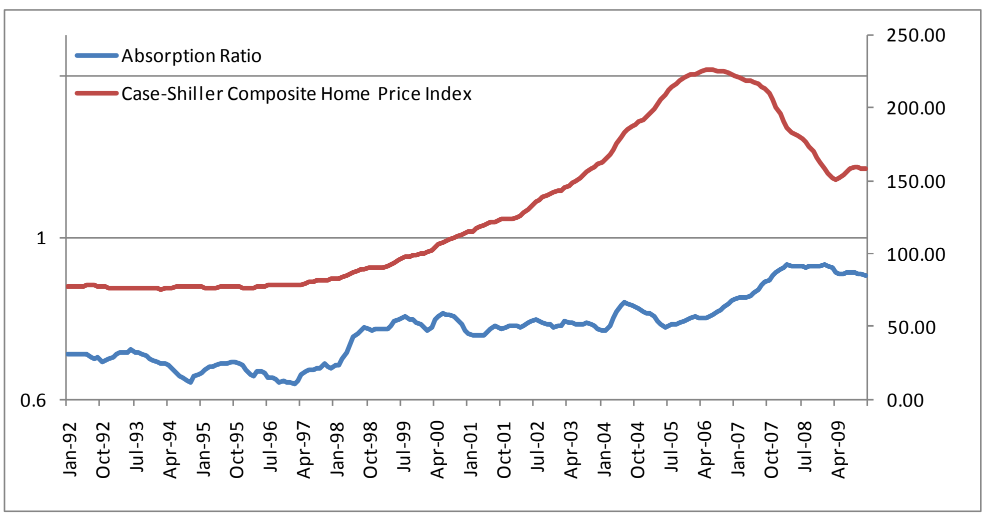


The Absorption Ratio and the Housing Bubble

Former Federal Reserve Chairman Alan Greenspan stated that although regional housing markets often showed signs of unsustainable speculation resulting in local housing bubbles, he did not expect a national U.S. housing bubble.[13] Had the Fed examined the absorption ratio of the U.S. housing market, they might have learned that regional housing markets were becoming more and more tightly coupled as early as 1998, setting the stage for a national housing bubble.

Exhibit 12 shows the absorption ratio estimated from 14 metropolitan housing markets in the United States, along with an index of the Case-Shiller 10-City National Composite Index.[14]

Exhibit 12: The Absorption and the National Housing Bubble



It reveals that the housing market absorption ratio experienced a significant step up from 64.12% in January 1997 to 77.68% in September 1998, just as the national housing bubble got

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[13] He has since rejected this view.

[14] The returns are computed from the Case-Shiller Indexes that go back to 1987. The metropolitan areas include : Los Angeles, San Diego, San Francisco, Denver, Washington, DC, Miami, Tampa, Chicago, Boston, Charlotte, Las Vegas, New York, Cleveland, and Portland. In this case, the covariance matrix is based on five years of monthly returns beginning January 1987 and ending December 2009, and the absorption ratio is based on the first three eigenvectors, roughly 1/5th of the number of assets.

underway. It reached another historic peak of 80.21% in July 1999 and then again in July 2004 at 83.77% as the housing bubble continued to inflate. It again reached an historic peak of 84.16% in December 2006 within a few months of the housing bubble peak. Then as the housing bubble burst, the absorption ratio climbed sharply, reaching at an all time high of 93.19% in March 2008. As housing prices stabilized and recovered slightly in 2009, the absorption ratio began to retreat modestly.

It is quite clear from this exhibit that systemic risk in the national housing market increased significantly leading up to the beginning stages of the housing bubble and as the bubble inflated, and that it increased even further after the bubble burst and housing prices tumbled.

The Absorption Ratio and Financial Turbulence

Now we turn to the relationship between systemic risk and financial turbulence. We define financial turbulence as a condition in which asset prices behave in an uncharacteristic fashion given their historical pattern of behavior, including extreme price moves, decoupling of correlated assets, and convergence of uncorrelated assets. We measure financial turbulence as:

$$d_t = (y_t - \mu)\Sigma^{-1}(y_t - \mu)' \qquad (2)$$

where,

d_t = turbulence for a particular time period t

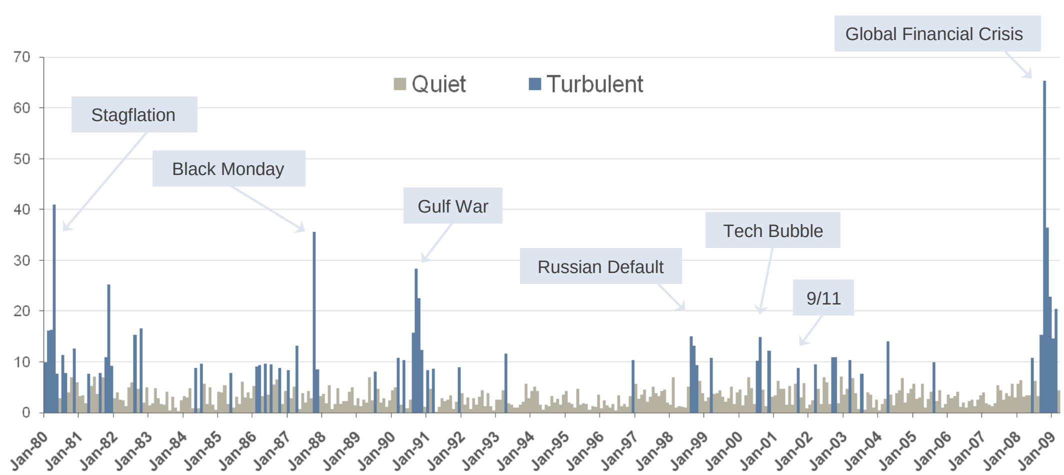
y_t = vector of asset returns for period t

μ = sample average vector of historical returns

Σ = sample covariance matrix of historical returns

Here is how to interpret this formula. By subtracting the historical average from each asset's return we capture the extent to which one or more of the returns was unusually high or low. By multiplying these differences by the inverse of covariance matrix of returns, we both divide by variance, which makes the measure scale independent, and we capture the interaction of the assets. By post multiplying by the transpose of the differences between the asset returns and their averages, we convert this measure from a vector to a single number. Previous research has shown that this statistical characterization of financial turbulence is highly coincident with events in financial history widely regarded as turbulent, as shown in Exhibit 13.[15]

Exhibit 13: Financial Turbulence[16]

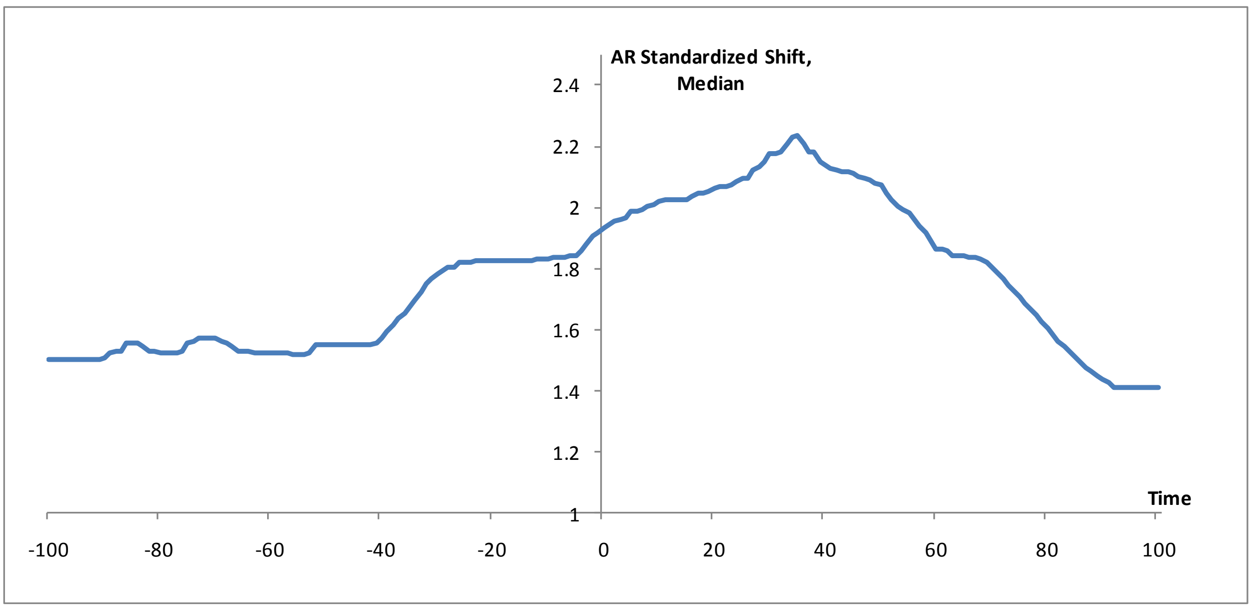


[15] For more about this measure of financial turbulence, including its derivation, empirical properties, and usefulness, see Kritzman, M. and Y. Li, "Skulls, Financial Turbulence, and Risk Management," forthcoming, *Financial Analysts Journal*

[16] This index of financial turbulence is based on daily returns of global stocks, bonds, real estate, and commodities.

In order to measure the connection between systemic risk and financial turbulence, we first identify the 10% most turbulent 30-day periods, based on average daily turbulence, of the MSCI USA stock index covering the period from January 1, 1997 through January 10, 2010. We then synchronize all these turbulent events and observe changes in the 15-day absorption ratio relative to the one-year absorption ratio estimated from industry returns as described earlier, leading up to and following the turbulent events. Exhibit 14 shows the results of this event study.

Exhibit 14: Median Absorption Ratio around Turbulent Periods



The median of the standardized shift in the absorption ratio increased beginning about 40 days in advance of the onset of the turbulent period, and continued to rise throughout most of the period, peaking a few days after the conclusion of the turbulent episode[17]. Moreover, the 15-day

[17] This continued rise is to be expected because we define the event as the beginning of the month over which we average daily turbulence, and because we know that turbulence is persistent.

moving average of the absorption ratio exceeded the one-year moving average in advance of 92% of the turbulent events, and 83% of the turbulent events were preceded by at least a one-standard spike. This evidence suggests that the absorption ratio is an effective precursor of financial turbulence, which could prove to be quite valuable. In addition to persistence, another feature of turbulence is that returns to risk are much lower during turbulent periods than non-turbulent periods.[18]

The Absorption Ratio and Global Financial Crises

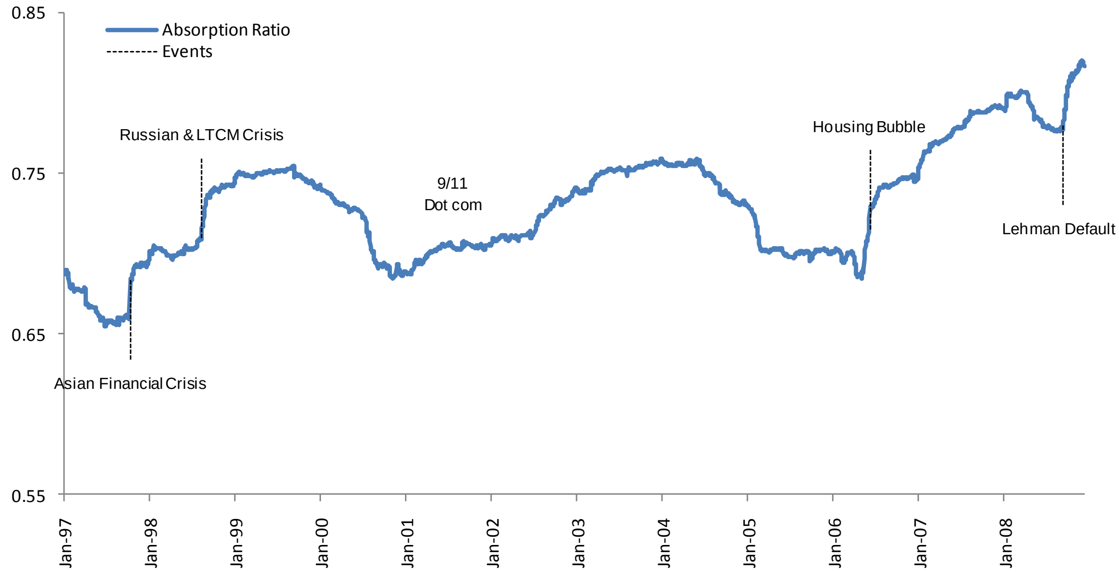
The previous subsections have looked at the performance of the absorption ratio in the domestic economy. We now analyze its implications in the global economy. To calculate the global absorption ratio, we collected daily stock market returns for 42 countries (and some regional indexes) from February 1995 to December 2009.[19]

Exhibit 15 shows that the global absorption ratio moved from 65% up to 85 percent during this period. Also, it shows that the global absorption ratio increased during October 1997 (Hong Kong's speculative attack after the Asian Financial Crises), and August of 1998 (Russian default and LTCM collapse), which were two of the most significant emerging market crises in the last 20 years. The other significant crisis was the Tequila crisis in 1994, but that is outside our sample.

[18] See Kritzman and Li, 2010.

[19] We used the first eight eigenvectors to estimate the absorption ratio, which equals about 1/4th the rank of the covariance matrix.

Exhibit 15: Global Absorption Ratio



During the recovery in emerging markets (1999-2001), the global absorption ratio decreased. It increased afterwards during the boom that followed the severe declines in interest rates that took place after September 11, the accounting standard scandals, and the Dot Com collapse in 2001. Finally, the last significant increase takes place starting in mid 2006 coinciding with the housing bubble, and then Lehman's default.

Clearly, the systemic risk during the recent crisis was much more pronounced than during the Asian and Russian crises, and the contagion that took place during the recovery.

An interesting aspect of the global absorption ratio is that it is highly correlated with structural measures of contagion. In Pavlova and Rigobon (2008), the authors provide a structural model in which asset prices are affected by financial constraints. In that model, the covariance of all asset prices co-moves with the degree of financial constraint. In fact, if all asset returns are measured on a common currency, then all the covariances move by the exact same amount. This provides a simple indicator of how contagion should take place.

Next we estimate the rolling covariance of the same 42 assets and concentrate on the average change of the covariance.

Exhibit 16: Global Absorption Ratio versus Change in Covariance

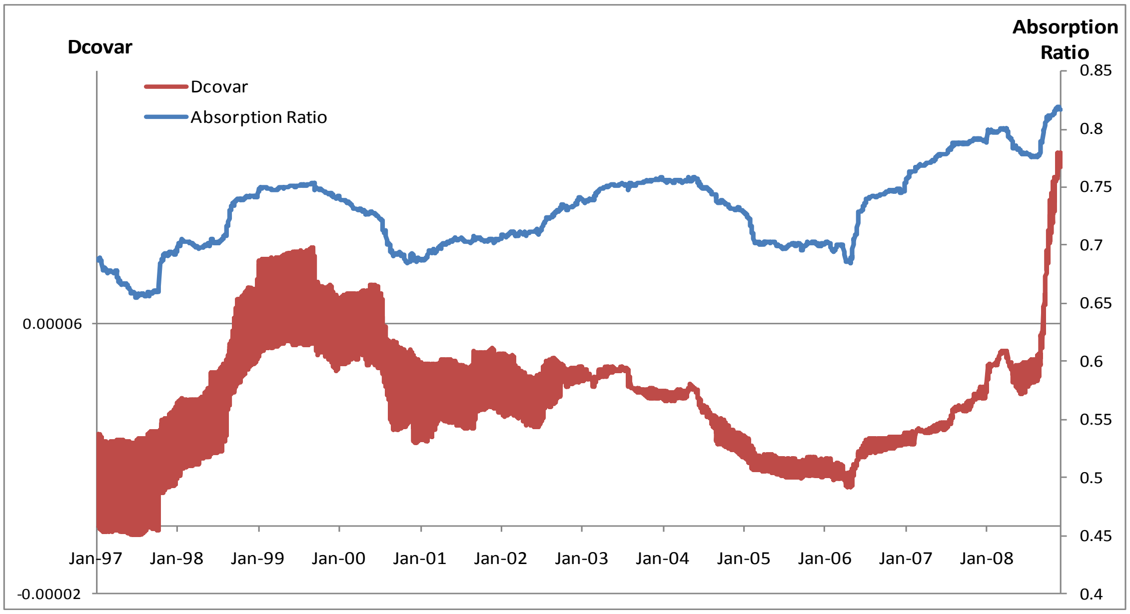


Exhibit 16 shows both the average change in the covariance and the global absorption ratio (same as exhibit 15). The change in the covariance is measured on the left vertical axis, while the variance is measured on the right hand side.

The two series are highly correlated, except during the boom, where the absorption ratio remained high, while the change in the covariance dropped significantly. The average change in the covariance is noisier (so noisy that the figure seems as if there is a region of estimates), but it is effective at capturing the contagious crises.

Exhibit 17: Global Absorption versus Smoothed Average Change in Covariance

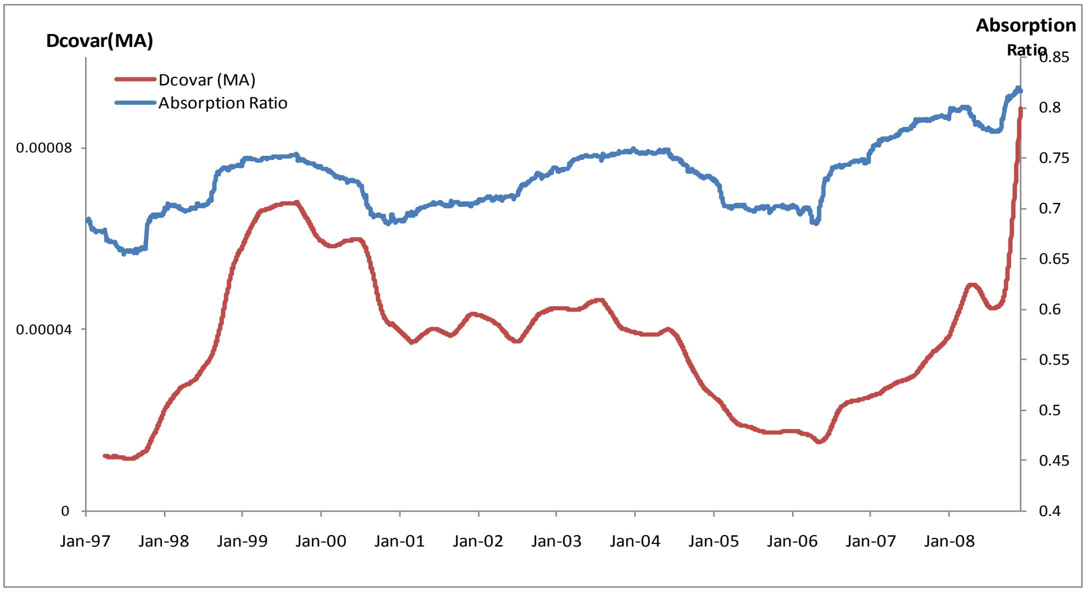


Exhibit 17 shows the moving average (500 days) of the average change in the covariance. The similarities with the global absorption ratio are striking. This comparison highlights that international contagion and systemic risk are closely related –it is comforting that the two measures are similar.

Part IV: Summary

We have introduced a method for inferring systemic risk from asset prices, which we call the absorption ratio. It is equal to the fraction of a set of assets' total variance explained or absorbed by a finite number of eigenvectors. A high absorption ratio implies that financial markets are relatively compact. When markets are compact they are more fragile, because shocks propagate more quickly and broadly. A low absorption ratio suggests that markets are less tightly coupled and therefore less vulnerable to shocks.

Compact markets do not always lead to asset depreciation, but most significant stock market drawdowns were preceded by spikes in the absorption ratio. This suggests that spikes in the absorption are a near necessary but not sufficient condition for market crashes.

We have shown that stock returns are much lower, on average, following spikes in the absorption than they are in the wake of significant declines in the absorption ratio and that investors could have profited by varying equity exposure following significant changes in the absorption ratio.

We have demonstrated that the absorption ratio of the U.S. housing market provided early signs of the emergence of a national housing bubble, long before the Fed recognized this fact.

We have presented evidence showing that increases in the absorption ratio anticipate subsequent episodes of financial turbulence as.

Finally, we have shown that variation in the absorption ratio coincided with global financial crises and independent measures of contagion. In short, the absorption ratio appears to serve as an extremely effective measure of systemic risk in financial markets.

We propose that regulators and investors create indexes of implied systemic risk defined as the absorption ratio (Equation 1) for various markets. We also think it would be informative to create indexes that capture shifts in the short-term absorption ratio relative to the long-term absorption ratio, as shown.

$$\Delta AR = (AR_{15\text{ Day}} - AR_{1\text{ Year}}) / \sigma \qquad (3)$$

where,

ΔAR = Standardized shift in absorption ratio

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

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

σ = standard deviation of one-year absorption ratio

These indexes of implied systemic risk might serve as early warning signals of potential asset depreciation and financial turbulence. With advance warning of the potential for trouble, policy makers and investors could take steps to prevent the potential from becoming the reality.

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