Systemic Risk, Financial Crisis and Vulnerability of Economy

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Abstract

We develop a measure of systemic risk of network of economic sectors, both financial and real sectors, based on symbolic transfer entropy (STE), by incorporating the strength and asymmetry of information flow and by calibrating the works of Billio and et. al. (2012). Investigating the time variation of systemic risk in the United States using size weighted index return of Fama and French 48 industries, we document that systemic risk of whole economy as well as financial sector start to increase beginning from the year 2001 and grow continuously until it reaches a peak in 2008. In addition, we find that systemic risk pops up during Asian and Russian currency crisis in 1998 albeit for short duration. In addition, we find that systemic risks are closely linked to the rest of the economy. We use a battery of macro-economic variables, and show our systemic risk measure is robust with unemployment, treasury rate, return and volatility of stock index among other macro-economic variables. Interestingly, the systemic risk in 2010 remains at same high level as in financial crisis period of 2007/2008.

Keywords: systemic risk, real and financial sector interaction, contagion, information flow

JEL Classification Number: G21, G24, G28

1 Introduction

Financial crisis in 2007/2008 highlights the vulnerability of real economy to financial sector meltdown, and creates keen interests of why, how and what happened to the financial sector and the whole economy, ultimately leading to the biggest and painful recession after the Great Depression in 1929. As a result of sudden unexpected financial crisis, the issue of how to prevent another potential crisis and crash in the future caught immediate interests for academics, practitioners, regulators and policymakers. Policy makers in the U.S. adopted one of the most stringent regulations in 2010, adopting Dodd-Frank Act.[1] Furthermore, regulators try to mend several weaknesses that might be responsible for the crisis. Requiring CDS to be traded through the Clearing House is one example. For academics, plethora of research, both theoretical and empirical, on different aspects of financial crisis added to the better understanding of the causes, processes of the current and past crises. Those researches have implications on several preventive and preemptive measures to forestall potential future crisis. One of key issues in the prevention of future crisis is the measurement problem. The relevant questions are as follows: what is the symptom that potentially leads to the crisis? Are there any measures that signals potential crisis? How to measure systemic risk?

While the idea of systemic risk is considered to be important and relevant in understanding the current crisis and the prevention of potential future crisis, there is no clear consensus on the concept and measurement of systemic risk. For example, Billio et. al. (2012) takes a viewpoint that A more formal definition is any set of circumstances that threatens the stability of or public confidence in the financial system., and analyze monthly returns of four types of financial institutions: hedge funds, and publicly traded banks, broker/dealers, and insurance companies. Lehar (2005) proposes to measure systemic risk, defined as the probability of a given number of simultaneous bank defaults, from equity return data. Avesani et al. (2006) and Basurto and Padilla (2006), among others, are examples of stress testing exercises on the financial sector

[1]Remind that the Sabanes-Oxley Act 0f 2002 was a response to the internet bubble and fraudulent behavior of internet firms in 1999.

using market-based information.

In this paper, we take much broader view of including whole economic system that includes financial sectors and real sectors in one networking framework. The challenge to incorporate wide range of economic sectors is how to identify and measure complex web of connection among firms, industrial and financial firms. Key components in the measurement of systemic risk are: connectedness, strength and direction of causality from one node to another in a network, degree of concentration of risk in a particular node or nodes, where nodes represent, in this paper, 48 industry group classified by Fama and French (1997). In addition, we capture sensitivities of the industry and the network to market prices and economic conditions. Billio et. al. (2012) empirically estimate the network structure of financial institutions generated by stock-return interconnections, by simply measuring correlation directly and unconditionally through principal components analysis and by pairwise Granger-causality tests and using these metrics to gauge the degree of connectedness of the financial system. We propose symbolic transfer entropy (STE) to capture not only connectedness, but also the direction and strength of causality. The advantage of STE is that our systemic risk measure uses the strength as well as asymmetry of information flow. Further, our systemic risk measure are flexible, i.e. we can measure systemic risk for one industry, for example banking industry, or we can measure systemic risk for financial sector comprising of three industry group of banking, insurance, and trading. Most importantly, as we use current market information such as daily stock return, we can measure up-to-date magnitude of systemic risk in almost real time at a reasonable computer time and costs.[2]

One of most striking results from the empirical analysis is that our measure not only identifies the current crisis and other past crisis in 1987, and 1997/1998 Asian and Russian crisis, but also we found that systemic risk started to increase continuously from 2001 leading to financial crisis in 2007/2008. In addition, we found that systemic risks are closely linked to the rest of the

[2]In this paper, we focus on three financial industry groups. However, with further calibration, we can apply symbolic transfer entropy (STE), and measure systemic risk by any level of aggregation. For example, we can calibrate SR measure, at a micro level, to a particular institution.

economy. We use a battery of macro-economic variables, and show our systemic risk measure is robust with unemployment, treasury rate, stock return and volatility of stock among other macro-economic variables. Survey literature on systemic risk and measurement is summarized in section 2. Our methodology, symbolic transfer entropy (STE), is described and discussed in section 3. Section 4 describes data and graphical and econometric results. Conclusion follows in section 5.

2 Literature review

The financial crisis in 2008 and 2009 which almost brought about the collapse of financial sector revitalized the concept of systemic risk while it is reviewed by De Bandt and Hartmann (2000). There are two types of systemic events, either horizontal or vertical one.[3] In a horizontal systematic event, the bad news or even failure of a financial institution bring about adverse effects on one or several other financial institutions in a sequential way like domino. We observed this phenomenon in the financial crisis in 2008-2009.[4] In a vertical systemic event, the failure of financial sector should adversely affect real sectors. The shock transfer could take the form of credit crunch or debt deflation.

There are two approaches to understand the issue of systemic risk and macro-prudential regulation: empirical macroeconomics based and financial market based approach. These two approaches have different methodologies, emphases, and purposes. Macroeconomics base approach focuses on the impact of systemic events on real economy while financial sector is considered as amplification mechanism.[5] Financial market based approach focuses on the financial market structure while it views macroeconomy as background. This approach puts more emphasis on the interaction among financial institutions, the nonlinear feedback effect, and the identification of individual institutions that are systemically important.

[3]This categorization of systemic events is originally introduced by De Bandt and Hartmann (2000). Refer to their paper for detailed explanation.

[4]See Brunnermeier (2009) to recall the chronological order of financial contagion.

[5]Refer to De Nicolo and Lucchetta (2010). Macroeconomics based approach helps us to better understand the fundamental linkage between the real economy and the financial sector, especially in the long run.

Three popular cross sectional measures of systemic risk are conditional value at risk(CoVaR) by Adrian and Brunnermeier (2010), distressed insurance premium(DIP) by Huang, Zhou, and Zhu (2011), and systemic expected shortfall(SES) by Acharya et al (2012). These measures aim at estimating the magnitude of losses when many financial institutions simultaneously fall into difficulty. CoVaR computes the value-at-risk (VaR) of financial institutions under the condition that other institution is in financial distress. DIP computes required insurance premium to cover the losses arising from distressed banking system. SES measures the expected loss to each financial institution under the poor performance of entire set of financial institutions. While these measures are useful when we know that financial institutions are in distress we cannot use them for the early warning of the advent of financial crisis in that these measures cannot distinguish the period of crisis from the period of non-crisis because all of them use conditional approach.

Our work is closely related to Billio et al (2012) who propose connection based measures of systemic risk in a network which is composed of 4 distinct types of financial institutions: bank, insurance, trading companies, and hedge funds. They propose two measures using well established econometric approaches: principal component analysis and pairwise Granger-causality tests. The rationale of this approach is that the more connected are financial institutions, the higher is systemic risk. This is based on the idea that linkage among financial institutions are the key element of systemic risk. This is based on the theoretical development which argues that financial crisis is more likely when the degree of correlation among the holdings of financial institutions is higher. They measure the connection between two financial institutions with Granger-causality of monthly stock returns. Their connection measure is of binary value (0 or 1) by applying the confidence level cut-off to Granger-causality tests.

We extend the network approach of Billio et al (2012) by introducing the strength and asymmetry of information flow between all nodes in a system and develop a measure of systemic risk utilizing all industrial sectors which include financial industries as well as industries in real sector. Their method of defining a binary connection by using the Granger causality test is not appropriate for fully understanding the systemic risk because the strength and asymmetry of interconnection is not reflected in binary network.

Figure 1 illustrates this idea. The directed network between three industry sectors in Figure 1 (a) delineates a network of symmetric information flow which could be easily observed in the binary Granger-causality network. The nodes represent industrial sectors. The links reflects the strength of information flow between industrial sectors. Figure 1 (b) demonstrates a network of asymmetric information flow which is the difference of information flow strength from i to j and from j to i. Because all three industries Granger-cause each other, this asymmetric network will be reduced to the binary network in Figure 1 (a) when we measure the connections between industrial sectors via Granger causality. But, Granger-causality test could not distinguish the network in Figure 1 (b) from that in Figure 1 (a). Figure 1 (c) and Figure 1 (d) display the network for the asymmetry of the information flow in Figure 1 (a) and Figure 1 (b), respectively. We call the network in Figure 1 (c) neutral economic system, i.e. the systemic risk will be zero because there are no asymmetry of the information flows. In Figure 1 (d), the network, reflecting the asymmetry of information flows, is quite different from the network shown in Figure 1 (c). To measure systemic risk, we consider an amount of the strength of information flow and its asymmetry feature using symbolic transfer entropy that can measure those then propose the novel approach to assess systemic risk.

3 Measure of Systemic Risk

In this section we introduce a measure of information flow which enables us to identify the source and sink nodes in a total economic system comprised of real and financial sectors.[6] Aiming at investigating the dynamic shock propagation in the total economic system during financial crisis period, we adopt the symbolic transfer entropy (STE) measure from Econophysics literature to quantify the information flow between two nodes and aggregate the pairwise information flow for a node from other nodes in the system to figure out whether the node plays a role of either

[6]The information flow could be considered as the direction of shock transmission.

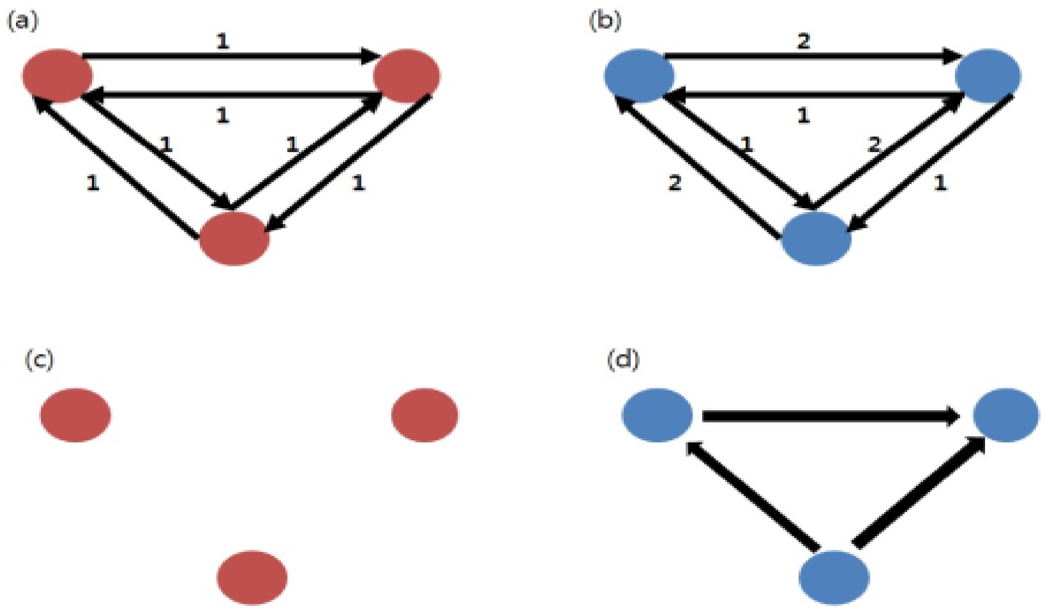


Figure 1: Network of the information flows between industry sectors and its asymmetry (a) Network structure of symmetric information flows (c) display a network topology for the asymmetry of the information flows, showing nothing completely on a connection. (b) In this example, network structure of symmetric information flows where the connections on this network show the strength and the direction of information flow. (d) demonstrate the network structure for asymmetry with the strength of information flow, showing it is quite different from the network in (c).

source or sink.[7] A source node has a positive aggregate information flow while a sink node has a negative aggregate information flow. We assume that internally or externally generated systemic shocks will move from source nodes to sink nodes. In other words, a source node can either generate a shock or transmit shock to a source or sink node while a sink node does absorb shocks or transfer shocks to other sink nodes according to the hierarchy of the network.

3.1 Symbolic Transfer Entropy

Staniek and Lehnertz (2008) extend the measure of information transfer of Schreiber (2000) by utilizing the technique of symbolization. The symbolic transfer entropy (STE) measure has some merits over the original transfer entropy measure in a couple of ways: symbolic transfer entropy is a more robust and very computationally fast method to quantify synchronization and complex interaction between dynamical systems than original transfer entropy method which is related to the causality measure of Granger (1969).[8]

In order to better understand symbolic transfer entropy, we need to know what transfer entropy is. Suppose we are interested in the interaction between X and Y systems and observe the sequences of variable x and y from the systems at $t = 1, 2, ...T$. The transfer entropy or information flow from Y to X system is defined in the following way

$$TE_{Y \to X} = \sum p(x_{t+1}, x_t, y_t) \log \frac{p(x_{t+1}|x_t, y_t)}{p(x_{t+1}|x_t)}, \tag{1}$$

where $x_t = x(t)$ and $y_t = y(t)$, $t = 1, 2, 3, ..., T$ represent the sequences of observations from systems X and Y at time t. The p indicates the transition probability density function. The joint probability density function $p(x_{t+1}, x_t, y_t)$ is the probability of three events, x_{t+1}, x_t, and y_t occurring in conjunction. The conditional probabilities $p(x_{t+1}|x_t, y_t)$ and $p(x_{t+1}|x_t)$ are the probabilities of some event x_{t+1} at time $t+1$, given the occurrence of the return x_t, y_t and x_t,

[7] In principle, we could have a neutral node whose aggregate information flow is exactly zero. But, the probability of the occurrence of neutral node is almost surely zero.

[8] See Barnett *et al.* (2009) for the relationship between transfer entropy and Granger causality. They show that transfer entropy is equivalent to Granger causality when variables are Gaussian.

respectively, at time t. Transfer entropy is the weighted sum of joint probability of three states where the weights are the log ratio of two conditional probabilities. If there is no information flow from Y to X, then X and Y must be independent or $p(x_{t+1}|x_t, y_t) = p(x_{t+1}|x_t)$ so that transfer entropy becomes zero by definition. Otherwise, Y is informative to predict the transition probability of state i from time t to time $t+1$. This measure is essentially asymmetric in that $TE_{X\to Y}$ could be different from $TE_{Y\to X}$.

Calculating symbolic transfer entropy (STE) involves the following two steps. First, we generate the symbolic time series from the original return series data using the symbolization technique.[9] We define symbols by reordering the amplitude values of return time series x_t and y_t. Given time delay τ and embedding dimension m, we rearrange the set of return sequences $X_t = \{x_t, x_{t+\tau}, ..., x_{t+(m-1)\tau}\}$ in an ascending order $\{x_{t+(k_{t1}-1)\tau} \leq x_{t+(k_{t2}-1)\tau} \leq ... \leq x_{t+(k_{tm}-1)\tau}\}$. This sequence of indexes is utilized to define a symbol $\hat{x}_t \equiv (k_{t1}, k_{t2}, ..., k_{tm})$. For example, a set of return sequences with embedding dimension 3 and time delay 1, {0.1, 0.4, 1.1}, is symbolized into (1,2,3) according to the position of ascending amplitude. Another set of returns sequences with different amplitudes but same ranks {-0.2, 0.3, 1.2} is identically symbolized into (1,2,3). When we have equal amplitude in the set, we ensure that every X_t has unique mapping onto one of the $m!$ permutations by figuring out the relevant indexes.[10] We can estimate the joint and conditional probabilities of the sequence of permutation indices with the relative frequency of symbols.

Second, we estimate transfer entropy using the symbolic time series data $\hat{R}^i_t$ and $\hat{R}^j_t$,

$$STE_{\hat{R}^i_t\to\hat{R}^j_t} = \sum p(\hat{R}^j_{t+\delta}, \hat{R}^j_t, \hat{R}^i_t) \log \frac{p(\hat{R}^j_{t+\delta}|\hat{R}^j_t, \hat{R}^i_t)}{p(\hat{R}^j_{t+\delta}|\hat{R}^i_t)}, \tag{2}$$

where $\hat{R}^i_t$ and $\hat{R}^j_t$ denote the symbolic time series at time t reconstructed with the embedding dimension m and time delay τ from the return time series r^i_t and r^j_t, respectively. The symbolic transfer entropy (STE), $STE_{R^i_t\to R^j_t}$, can quantify the amount of information flow from R^i_t to R^j_t.

[9] Refer to the concept of permutation entropy of Bandt and Pompe (2002) to concretely understand the symbolization technique.

[10] Suppose $x_{t+(k_{t1}-1)\tau}$ is equal to $x_{t+(k_{t2}-1)\tau}$. We write that $x_{t+(k_{t1}-1)\tau}$ is less than or equal to $x_{t+(k_{t2}-1)\tau}$ if k_{t1} is less than k_{t2}.

3.2 the measure of pairwise and aggregate information flow asymmetry

Compared to binary Granger causality network by Billio *et al.* 2012, our directionality measure has advantages over their methodology from the perspective of information flow. First, our directionality measure provides the strength of directionality while binary Granger causality network has three discrete levels of directionality of information flow from i to j, that is +1($i \rightarrow j$), 0(bidirectional feedback), and -1($j \rightarrow i$). Even though there is feedback effect between two institutions, it is possible that one institution weakly dominates the other in terms of influence. Our measure can detect this asymmetric information flow while the binary network cannot. Second, we can construct a network topology based on the strength of information flows which surpasses a certain threshold that are estimated by surrogate test method.

We consider the pairwise information flow using the STE, defined as

$$D^S_{i\rightarrow j} = STE_{R^i_t \rightarrow R^j_t} - STE_{R^j_t \rightarrow R^i_t} \tag{3}$$

If the pairwise information flow $D^S_{i\rightarrow j}$ has a positive value, R^i_t is a driving force for another process R^j_t, while if it has a negative values, R^j_t drives R^i_t. We call i and j pairwise source and sink each if the pairwise information flow, $D^S_{i\rightarrow j}$ takes a positive value. In the case that R^i_t and R^j_t follow independent and identically distributed (IID) processes, that is, $\frac{p(R^j_{t+\delta}|R^j_t, R^i_t)}{p(R^j_{t+\delta}|R^i_t)} = 1$, then the STE, $T_{R^i_t \rightarrow R^j_t}$, is also zero. That is, there is no information flow when two processes are random.

We define another information flow which accounts for the aggregate information flow from one institution (industry sector) to all other institutions (industry sectors) in a system. Suppose that there are N institutions in a system S. First, we define outward information flow from institution i to all other institutions in S. For the brevity of expression, we define alternative representation of symbolic transfer entropy: $STE_{R^i_t \rightarrow R^j_t} \equiv STE_{i\rightarrow j}$.

$$IF^{out}_i = \frac{1}{N-1} \sum_{i \neq j} STE_{i\rightarrow j}$$

The inward information flow to institution i from all other institutions is defined by the following equation:

$$IF_i^{in} = \frac{1}{N-1} \sum_{i \neq j} STE_{j \to i}$$

Then, we define the aggregate asymmetric information flow of an individual institution i by taking the difference between outward information flow from the institution i and inward information flow to the institution i.

$$AIF_i = \frac{IF_i^{out} - IF_i^{in}}{1/N(N-1) \sum_i \sum_{j \neq i} STE_{i \to j}} \tag{4}$$

If the aggregate information flow (AAIF) of institution i is positive (negative), then the institution plays the role of information source (sink) of the system. The AAIF measure spans from -1 to +1. Two boundary cases occur when all institutions in a system S form a star network where only one institution i is connected with all other institutions $j(\neq i)$ and all directions of information flow from i to j are the same. The AIF of institution i takes the value of +1 (-1) in case that the direction of information flow is outward from (inward to) i.

3.3 the measure of systemic risk

In nature, the movement of particles is produced when difference in potential energy between any two places at the same space is great and the flow of the river was also streamed when there is an asymmetry between inflows and outflows in any place as well. Likewise, when the asymmetry of information inflows and outflows in the economic system increases, information will flow more quickly, but when there is no difference between inflows and outflows in all sectors the information flow is stagnant, i.e. the financial system have become significantly more stable. Thus, the asymmetry of information flows between industrial sectors should play an important role in terms of the diagnosis of market stability as well as the measuring systemic risk induced from information flows on the economic network.

We focus on investigating the impact of both the strength and asymmetry of the information flow on the level of systemic risk. To propose the novel measure for the systemic risk in the whole economy system, two concepts that should be linked closely to measuring systemic risks, such as the interconnectedness and the asymmetry were used. These features in the economy network constructed by the information flows will reflect the principal concept which is able to explain the fundamental mechanism of the causes of systemic risk.

When an institution is independent of all other institutions, then both pairwise and aggregate information flow of the institution is zero. This independent institution does not contribute to the systemic risk because it cannot transmit the shock generated by one institution to other institutions. The most stable system with the least likelihood of systemic events is a collection of independent institutions without any source and sink in the system.

When aggregate information flow of an institution is zero, the institution marginally increase systemic risk because it just plays the role of relay which transfer all shocks it absorbed from other institutions to other institutions at the same amount thus it does not carry the risk of failure itself. However, an institution i in a system S start increasing the system wide risk when it plays the role of either aggregate source or aggregate sink. Systemic risk will increase as we have more aggregate sources and aggregate sinks in the system. Let's first consider the pair of a global source and a global sink institutions. This pair can serve as a path through which shocks can be transmitted. As we have more this kind of paths, it is more likely that the shocks transmit further though the chain of relays like domino effect. If this chain finally ends up with a ring, then we observe a feedback which will have a larger impact on the systemic risk.

We postulate that both the pair of source-source and sink-sink will have less impact on systemic risk in that it is less likely to have a path through which shocks are transmitted in comparison of source-sink pair. In the extreme case, the pair of source and source cannot contribute to the systemic risk when the pairwise information flow of the two institutions is zero. one idea for the relative contribution to systemic risk is that only source (sink) institutions matter. Another we are not sure whether aggregate source contributes more than a sink to the systemic risk. To investigate this, we draw a scatter plot to investigate the relationship between the measure of systemic risk and asymmetric information flow. Figure 2 shows that there exist

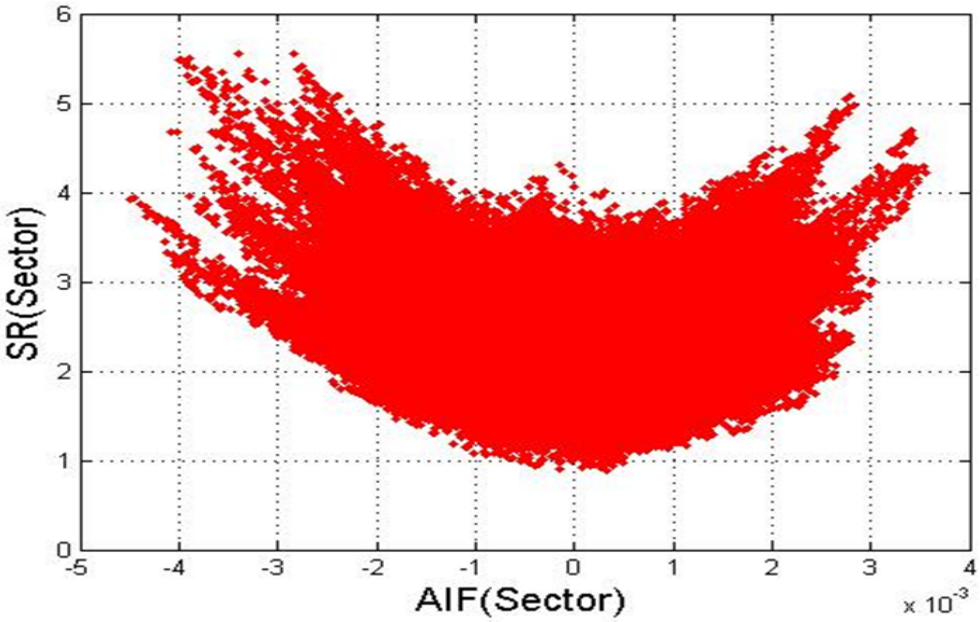
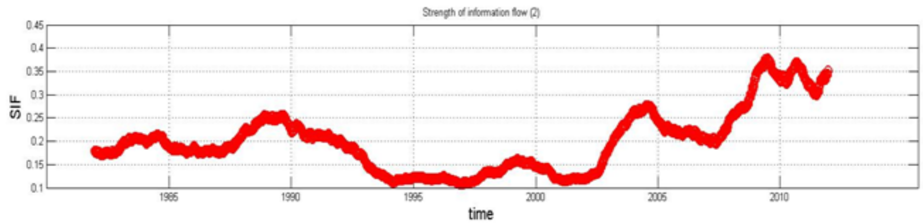


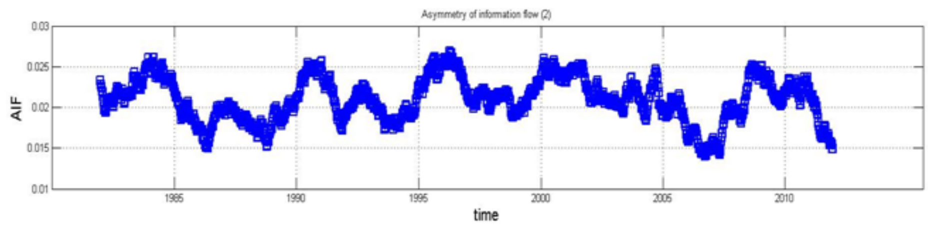
Figure 2: Convex relationship between the measure of systemic risk and asymmetric information flow

a convex relationship between the measure of systemic risk and asymmetric information flow. This convex relationship implies that the source and sink in a source-sink pair seem to have equal contribution to systemic risk. This observation helps us to refine the definition of our systemic risk measure.

When we have multiple source and sink institutions in a economic system, we have three distinct types of connections: source-source, source-sink, and sink-sink connections. We consider the source-source connection. We are interested in the pairwise information flow between two source nodes i and j or $PIF_{i \to j} = IF_{i \to j} - IF_{j \to i}$. If the pairwise information flow between i and j is close to zero, then it means that two source nodes behave independently. Regardless of the types of connection between two nodes, we denote the independency between two nodes by drawing no line between them. Instead one source node i act a source and the other j node act a sink in a pair when the pairwise information flow is highly positive and vice versa. We draw a directed line from i to j to illustrate the presence and direction of information flow.



(a) Evolution of the strength of information flow



(b) Evolution of the asymmetry of information flow

Figure 3: Evolution of the strength information flow and information asymmetry

We examine the time evolution of strength and asymmetry of information flow. The strength of information flow is measured by the total summation of information among all nodes, $SIF = \sum_i \sum_{j \neq i} (IF_{i \to j} + IF_{j \to i})$. The total asymmetry of information flow is measured by the total summation of asymmetric information flow, $AIF = \sum_i \sum_{j \neq i} (IF_{i \to j} - IF_{j \to i})$.

Top (bottom) panel of Figure 3 illustrates the time evolution of the strength (asymmetry) of information flow. The strength of information flow shows highly dynamic pattern, middle range in the 1980s, low range in the 1990s, and high range in 2000s. The variation in the strength of information flow seems to capture the main

The diagram above illustrates the importance of the source-sink information flow. We materialize the conceptual importance of source-source information flow with the following equation.

$$SR(t) = \frac{1}{N(N-1)} \sum_i \sum_{j \neq i} (IF_{i \to j} + IF_{j \to i}) \cdot W_{ij} \tag{5}$$

where the weight is the product of asymmetric information flow of node i and j and the difference between two pairwise information flow or $W_{ij} = |AIF_i||AIF_j|(IF_{i \to j} - IF_{j \to i})$. The asymmetric information flow in the definition is distinct from the the definition of asymmetric information flow defined by Equation 4. We use the following equation to define a new asymmetric information flow

$$AIF_i = \frac{\sum_{j \neq i} IF_{i \to j} - IF_{j \to i}}{\sum_i \sum_{j \neq i} IF_{i \to j}} + 1 \tag{6}$$

4 Empirical analysis

4.1 Data

We use daily returns of public stocks between Jan 1 1980 and Dec 31 2011 to construct value weighted index returns for 48 industrial sectors adopting Fama and French (1997) categorization for the following analysis. Financial sectors is composed of banking(industry group #44), insurance(# 45), and trading industries(# 47). We denote all other manufacturing and service industries except for financial sectors as real economic sectors. To investigate the temporal evolution of systemic risk, we constructed a sequence of network's from the moving trading days and examined the temporal evolution of network structure. We segmented the 48 industry sector time series into 1-year windows moving at 1 day and then calculated the network structure of information flows created using STE method. The created network for each sub-period is a set of significance network connections in terms of the path of information flow, which can be shown as level of systemic risk induced by network topology over time.

We retrieve macroeconomic variables with Federal Reserve Economic Data (FRED) at Federal Reserve Bank of Saint Louis: three month treasury bill rate, ten year treasury bond rate, London interbank offered rate (LIBOR), S&P 500 index returns of daily frequency and unemployment rate of monthly frequency.

Table I reports the descriptive statistics of systemic risk measure, three month treasury bill, London Interbank Offered Rate(LIBOR), S&P 500 index returns, unemployment rate.

Table I: Descriptive Statistics

We provide the descriptive statistics of systemic risk measure and macroeconomic variables we link to the systemic risk in the following analyses. Macroeconomic variables include three month treasury rate, London interbank offered rate (LIBOR), the return and volatility of S&P 500 index of daily frequency, and unemployment rate of monthly frequency.

	Mean	Median	Std. Dev.	Max	Min	Mean	Median	Std. Dev.	Max	Min
	Panel A: Systemic risk					Panel B: Unemployment rate				
1982-1987	103.03	102.14	5.97	122.61	91.50	7.97	7.40	1.49	10.80	5.70
1988-1993	102.51	100.57	10.28	131.11	81.18	6.25	6.50	0.88	7.80	5.00
1994-1999	89.65	88.95	5.26	105.59	78.50	5.10	5.15	0.69	6.60	4.00
2000-2005	100.75	99.77	13.45	132.58	79.24	5.15	5.40	0.72	6.20	3.90
2006-2011	122.20	122.19	11.53	147.88	97.87	7.31	8.70	2.29	10.00	4.40
	Panel C: Three month T-bill rate					Panel D: London Interbank Offered Rate				
1982-1987	8.30	8.10	2.20	15.49	5.18	7.01	7.00	0.73	9.31	5.63
1988-1993	5.86	6.00	2.08	9.45	2.67	6.44	6.88	2.32	10.63	3.13
1994-1999	5.01	5.13	0.56	6.07	2.98	5.50	5.63	0.58	6.50	3.25
2000-2005	2.79	1.99	1.79	6.42	0.81	3.08	2.19	1.92	6.87	1.00
2006-2011	1.84	0.22	2.10	5.19	0.00	2.47	1.45	2.18	5.73	0.25
	Panel C: Return of S&P500 index					Panel F: Volatility of S&P500 index				
1982-1987	0.13	0.16	0.15	0.46	-0.26	9.08E-05	7.72E-05	6.80E-05	4.56E-04	4.00E-05
1988-1993	0.08	0.09	0.11	0.30	-0.26	1.26E-04	7.62E-05	1.42E-04	4.92E-04	2.94E-05
1994-1999	0.18	0.19	0.10	0.40	-0.04	8.27E-05	5.36E-05	5.80E-05	2.01E-04	2.24E-05
2000-2005	-0.02	0.05	0.17	0.36	-0.42	1.49E-04	1.68E-04	7.76E-05	3.01E-04	4.11E-05
2006-2011	0.01	0.08	0.22	0.52	-0.67	2.22E-04	1.31E-04	2.45E-04	8.29E-04	3.46E-05

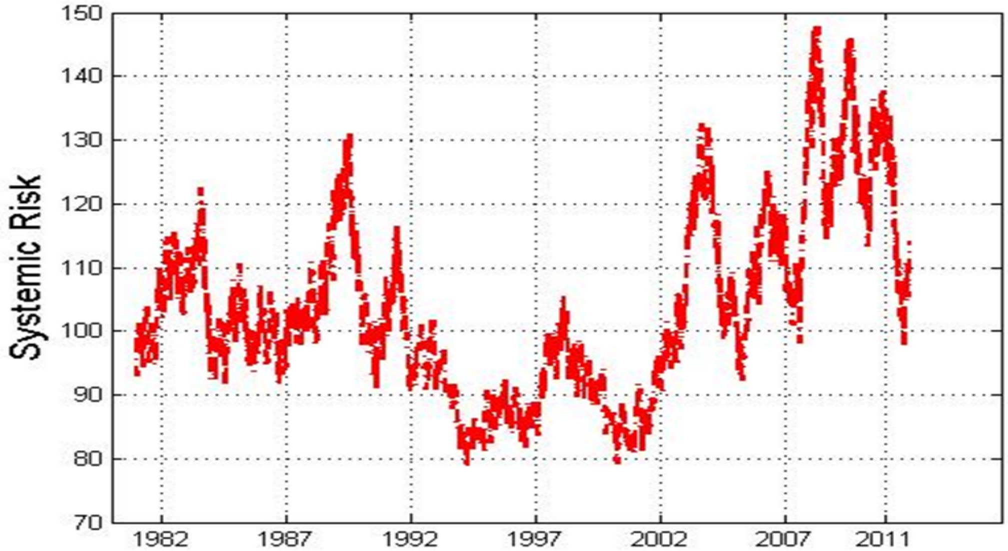


Figure 4: Time evolution of systemic risk measure

4.2 Evolution of systemic risk

Figure 4 illustrates the time evolution of systemic risk with our measure. It is easily seen that the magnitude of systemic risk waxes and wanes over time. The level of systemic risk moderately oscillates in 1980s until it climbs up to a peak in period of Black Monday in 1987. Systemic risk level climbs down in the early 1990s to reach the lowest level in 1994 and subsequently maintains much lower level in late 1990s until it bumps up to a peak which seemingly matches with Russian and Asian crisis in late 1990s. More interestingly, our systemic risk measure indicates that there is a turning point in early 2000s in that systemic risk measure continued to grow after 2001 until it reached a peak in 2008 while it keeps falling after 1997 Russian fiscal crisis until 2001. The height of systemic risk maintains the highest level during 2008 and 2010.

The graph above shows that the sharp increase in our systemic risk measure coincides with several identified crisis periods. Systemic risk reaches local peaks around 1987 LTCM crisis, 1997 Russian crisis, 2008 financial crisis. These matches between crisis periods and high systemic risk levels hint the good quality of our measure to detect real crises in the US economy.

4.3 Systemic risk and macroeconomic variables

We examine the relationship between our systemic risk measure and some macroeconomic variables, which are categorized into economic and financial ones. Financial macroeconomic variables include three month treasury bill rate, ten year treasury bond rate, and LIBOR rate, and the TED spread, and the return and volatility of S&P 500 index. Economic macroeconomic variable encompasses monthly unemployment rate. We run the simple regression of systemic risk measure on each macroeconomic variable. The estimation model is followed:

$$SR_t = \alpha + \beta \cdot macroeconomicvariable + \epsilon_t$$

Table II presents the results of regressing systemic risk measure on three month treasury bill rate and LIBOR separately. The analysis start at 1982. Left panel of Table II shows that there exists systematic change in the relationship between systemic risk and three month treasury rate. Systemic risk and T-bill rate are negatively correlated in 2000s while they are positively correlated in 1980s and 1990s. Especially, there are two subperiods when the relationship between the two are more significant than other periods: 1988-1993 and 2000-2005. The beta coefficient and t-statistics in 1988-1993 period are 0.754 and 44.405 while those in 2000-2005 period are -0.765 and -45.957. Especially, the three month T-bill continued to fall after 9.11 in 2001 to boost the US economy. This implies that the systemic risk might be elevated due to the continuous fall of short term interest rate or cheap credit.

Right panel of Table II also shows that systemic risk measure and LIBOR are negatively correlated in 2000s while they are positively correlated in 1980s and 1990s, which is similar to the relationship between systemic risk and T-bill. Especially, there are two subperiods when the relationship between the two are more significant than other periods: 1988-1993 and 2000-2005. The beta coefficient and t-statistics in 1988-1993 period are 0.776 and 47.486 while those in 2000-2005 period are -0.754 and -44.105.

Table III presents the results of regressing systemic risk measure on the return and volatility

Table II: The relationship between the measure of systemic risk and short term interest rates

We examine the relationship between our systemic risk measure and short term interest rates: three month treasury bill rate and LIBOR over different periods of time. The estimation model is followed:

$$SR_t = \alpha + \beta \cdot short\ term\ interest\ rate + \epsilon_t$$

	Variable: 3 Month T-bill rate				Variable: LIBOR			
Periods	observation	beta	t-statistic	R^2	observation	beta	t-statistic	R^2
1982-1987	1496	0.402	16.97	0.16	498	0.489	12.48	0.24
1988-1993	1501	0.754	44.41	0.57	1493	0.776	47.49	0.60
1994-1999	1500	0.155	6.09	0.02	1488	0.284	11.43	0.08
2000-2005	1497	-0.765	45.96	0.59	1479	-0.754	-44.11	0.57
2006-2011	1498	-0.420	17.90	0.18	1482	-0.356	-14.66	0.13

of S&P500 index separately. Left panel of Table III shows that there exists systematic change in the relationship between systemic risk and the return of S&P500 index. They are positively correlated before the financial crisis period while they are negatively correlated between 2006 and 2011. This positive relation implies that the increase in systemic risk of total economy has been compensated by higher return in equity index. However, the increase in systemic risk is penalized by lower return in a really big crisis. Right panel of Table III also shows that systemic risk measure and volatility of S&P500 index are positively correlated all times except one period between 2000 and 2005. It is really interesting that equity index volatility looks to be linearly independent of systemic risk measure while those two are a measure of risk, which means that they should be related in principle. Right panel of Table IV also display that systemic risk measure and TED spread, which is defined by the difference between the 3 month LIBOR rate and the 3 month Treasury rate, are positively correlated all time except one period from 2000 to 2005. In particular, although TED spread, which is a gauge deemed credit risk in the general economy, show a lower value during the period from 2000 to 2005, the systemic risk flourish continuously in same period, i.e. they are negatively correlated. It is quite interesting that we are not aware of fundamental risk relating to subprime crisis with a traditional measure.

In Table IV, we investigate the relationship between systemic risk and unemployment rate

Table III: The relationship between the measure of systemic risk and equity market index

We examine the relationship between our systemic risk measure and equity market index or the return and volatility of S&P500 index over different periods of time. The estimation model is followed:

$$SR_t = \alpha + \beta \cdot equity\ index + \epsilon_t$$

	Variable: index return				Variable: index volatility			
Periods	observation	beta	t-statistic	R^2	observation	beta	t-statistic	R^2
1982-1987	1517	-0.032	-1.24	0.00	1517	0.298	12.15	0.09
1988-1993	1518	0.115	4.49	0.01	1518	0.218	8.70	0.05
1994-1999	1515	0.583	27.93	0.34	1515	0.577	27.45	0.33
2000-2005	1508	0.264	10.63	0.07	1508	-0.019	-0.75	0.00
2006-2011	1509	-0.320	-13.12	0.10	1509	0.448	19.48	0.20

and TED spread in the US economy, respectively. In left panel of Table IV there exists systematic change in the relationship between systemic risk and the return of S&P500 index. They are positively correlated before the financial crisis period while they are negatively correlated between 2006 and 2011. This positive relation implies that the increase in systemic risk of total economy has been compensated by higher return in equity index. However, the increase in systemic risk is penalized by lower return in a really big crisis. Systemic risk measure and volatility of S&P500 index are positively correlated all times except one period between 2000 and 2005. It is really interesting that equity index volatility looks to be linearly independent of systemic risk measure while those two are a measure of risk, which means that they should be related in principle.

5 Conclusion

We develop a measure of systemic risk based on the strength and asymmetry of information flow measured by symbolic transfer entropy (STE), which incorporates the contribution from both financial and real sectors. When we investigate the evolution of systemic risk in the United States using size weighted index return of 48 industries based on Fama and French 1997, our measure coincides with the financial crisis between 2007 and 2009. Our systemic risk measure

Table IV: The relationship between the measure of systemic risk and unemployment rate

We examine the relationship between our systemic risk measure and unemployment rate over different periods of time. The estimation model is followed:

$$SR_t = \alpha + \beta \cdot unemployment\ rate + \epsilon_t$$

	Variable: unemployment rate				Variable: TED spread			
Periods	observation	beta	t-statistic	R^2	observation	beta	t-statistic	R^2
1982-1987	45	0.657	5.71	0.43	498	0.54	14.01	0.29
1988-1993	47	-0.631	-5.46	0.40	1493	0.67	34.54	0.45
1994-1999	46	-0.657	-5.78	0.43	1488	0.40	16.87	0.16
2000-2005	46	0.782	8.31	0.61	1479	-0.47	-20.08	0.22
2006-2011	47	0.315	2.23	0.10	1482	0.16	6.06	0.024

indicates that there is a turning point in 2001 in that systemic risk has built up since 2001 until it reaches a peak in 2008.

We investigate the relationship between the our systemic risk measure and macroeconomic variables. Three month treasury bill rate, LIBOR rate, and Federal Funds rate are positively associated with systemic risk measure in 1980s and 1990s while they are negatively associated in 2000s. This implies that the systemic risk might be elevated due to the continuous fall of short term interest rate or cheap credit. It is interesting that the market risk measured by the volatility of S&P 500 index and the TED spread is positively related to all other subperiods except for 2000-2005 subperiod when systemic risk kept rising while short term interest rate continued to fall. Unemployment rate is negatively related to systemic risk in 1980s and 1990s whereas unemployment rate is positively related to systemic risk in 2000s, which is the opposite pattern to the relationship between short term rate and systemic risk.

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