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Measuring Systemic Risk: Empirical Evidence on US Banks

Hung-Chun Liu,
Department of Finance,
Minghsin University of Science and Technology, Taiwan.

Yuan-Teng Hsu,
Yuan Ze University,
School of Management, Taiwan.

Jying-Nan Wang,
Department of Applied Economics,
Fo Guang University, Taiwan.
E-mail: jyingnan@gmail.com

Abstract

Due to the financial crisis and the sovereign debt crisis, how to measure the systemic risk becomes an important issue in the mainstream of financial econometrics. In this paper, we propose a measure for systemic risk and name it as CSRISK index, which expresses the worst capital shortfall of a financial institution conditional on a substantial market decline. This index only needs public financial data including accounting and market trading information, thus it is quick and inexpensive. Furthermore, the sum of all institutions' CSRISKs in the whole financial system represents an early warning indicator for the banking supervisor. The quantile regression approach is introduced to estimate the CSRISK. We use 238 U.S. banks from 2003 to 2013 as the empirical sample. Although traditional risk measures correspond lots of risk components, but the empirical results indicate that the CSRISK can provide some omissive information. Besides, all banks indeed produce the largest CSRISK during the financial crisis of 2008-2009. In terms of the market CSRISK, we find it is increasing from 2004 to 2009 and then is slightly decreasing. This systemic risk measure can potentially be widely applied in the practical risk management and macro prudential policy making.

Key words: *Systemic risk, Capital shortfall, Value at Risk, Quantile regression*
JEL Classification: *G18, G20, C20*

1. Introduction

De The financial crisis of 2008–2009 and the sovereign debt crisis of 2010–2012 bring several severe impacts of the financial system and the broader economy. These events have motivated banking supervisors, practitioners, and academics to pay more attention to the systemic risk. In the recent survey, Bisias et al. (2012) and Brunnermeier and Oehmke (2012) categorize and contrast quantitative measures of systemic risk in the economics and finance literature. One type of these approaches is to measure co-dependence in the tails of individual firms and the whole economy. Adrian and Brunnermeier (2011) propose the CoVaR[1] to measure systemic risk by the spillover effects from individual equities to the whole economy; Acharya et al. (2010) use the systemic expected shortfall (SES) to capture the downside risk when the whole market is in crisis. Other recent studies related to systemic risk include, for example, contingent claims analysis (Kritzman and Li, 2010; Gray and Jobst, 2011), granger-causality network model (Boyson et al., 2010; Bisias et al., 2012; Aragon and Strahan, 2012), and stress tests (Alfaro and Drehmann, 2009; Duffie, 2011).

First of all, we need to identify the meaning of systemic risk. Note that the systemic risk is different to the systematic risk. Systematic risks generally represent macroeconomic or market risks induced by certain aggregate shocks. However, the formal definition of systemic risk is much less clear than systematic risk, see Hansen (2012). One definition provided by Billio et al. (2012) is “any set of circumstances that threatens the stability of or public confidence in the financial system”. Similarly, Daniel Tarullo, the Governor of the United States Federal Reserve, defines the systemic risk[2] as follows,

“Financial institutions are systemically important if the failure of the firm to meet its obligations to creditors and customers would have significant adverse consequences for the financial system and the broader economy.”

In this definition, the core problem of the systemic risk is that the financial institutions bankruptcies or near bankruptcies makes negative externalities to the whole economy. In other words, when the market value of a financial institution’s equity falls to a significantly small proportion of its outstanding liabilities, its capital falls short and it has certain systemic risk.

In this research, we follow the above definition of systemic risk. Based on this point, Acharya et al. (2010) show that the systemic risk of a financial institution contains three

[1] A number of papers apply and extend the CoVaR for many financial markets. For example, Boyson et al. (2010) find strong evidence of worst return contagion across hedge fund styles; Chan-Lau (2009) apply CoVaR in the CDS of Asia-Pacific banks; the systemic risk of the Canadian banking system is estimated in Gauthier et al. (2012).

[2] *“Regulatory Restructuring,”* Testimony before the Committee on Banking, Housing, and Urban Affairs, U.S. Senate, Washington, D.C., July 23, 2009.

components: the real social cost of a crisis per dollar of capital shortfall, probability of a crisis, and expected capital shortfall of the firm in a crisis. Brownlees and Engle (2012) focus on the third component, which captures many important characteristics of systemic risk such as size, leverage, and interconnectedness. They provide the SRISK index which is the expected capital shortfall of a firm conditional on a substantial market decline. Furthermore, they have implemented this model based on publicly available data to measure the systemic risk of each financial institution. The results of their analysis are posted on the V-Lab web page at New York University (http://vlab.stern.nyu.edu/welcome/risk).

The primary motivation of this project is quite clear and meaningful. Because the SRISK is the expected capital shortfall of a firm conditional on a substantial market decline, it may overlook the tail-comovement effect of the individual financial institution and whole financial system. To be more precise, when the financial market is in distress, it is natural that each financial institution usually has larger capital shortfall. Therefore, in this project, we extend the SRISK index and propose a new systemic risk measure that can provide further information about the tail-comovement. This new systemic risk measure is denoted as the qth-quantile capital shortfall conditional on a substantial market decline. In this project, we focus on the worst capital shortfall (q = 0.01) and name it as the CSRISK. Comparing with SRISK, for example, when a financial institution's SRISK is $1,000 million, it represents its average capital shortfall is $1,000 million conditional on a market decline. However, the capital shortage of this financial institution has a high probability to be larger than $1,000 million. The CSRISK could be regarded as a more conservative systemic risk indicator. When the value of CSRISK (q = 0.01) is $1,000 million, it indicates that the capital shortage of this financial institution has only 1% probability to exceed the $1,000 million.

The CSRISK retains two advantages of SRISK. First, the CSRISK also merges both accounting and market trading information of a financial institution. The accounting value of institution's liabilities is easily available in the balance sheets and the market trading data could measure the market value of its equity immediately. Thus, this approach is quick and inexpensive. Secondly, the sum of every financial institution's CSRISK in the whole financial system could represent the aggregate systemic risk which could be an early warning indicator for the banking supervisor in policy making. Nevertheless, the CRSISK is more flexible than SRISK. Although we focus on the worst capital shortfall conditional on a market decline, the CSRISK with q = 0.5 could provide the similar information of systemic risk as SRISK. In this project, we adopt the quantile regression approach; see Koenker and Bassett (1978) and Koenker (2005), to estimate CSRISK. The quantile regression can estimate the various qth-quantile capital shortfalls conditional on a substantial market decline efficiently.

The rest of this proposal is organized as follows. Section 2 introduces our model related to the capital shortfall and shows the definition of CSRISK. How to estimate CSRISK through the quantile regression approach is represented in Section 3. Then Section 4 describes our empirical results. Section 5 shows the conclusions of this paper.

2. Capital Shortfall and CSRISK

When the capital shortfall of each financial institution occurs during a period of distress for the whole financial system, Acharya et al. (2010) propose an economic model to formally link these capital shortfalls and systemic risk. In their model, each firm's contribution to systemic risk denoted systemic expected shortfall (SES), can be measured and priced. However, this approach cannot be used for ex-ante systemic risk measurement. Brownlees and Engle (2012) extend the SES approach and propose an alternative dynamic reduced estimation strategy. They provide the SRISK index which is the expected capital shortfall of a firm conditional on a substantial market decline. The SRISK index depends on the firm's degree of leverage, size and equity loss conditional on a market decline that is denoted as the Marginal Expected Shortfall (MES). For computing the SRISK index, people not only need the information on the equity and debt which can be easily measured, but also require an appropriate econometric approach to estimate the MES from return data. Brownlees and Engle (2012) introduce a bivariate dynamic time series model for the daily firm and market returns. Their approach includes volatility and correlation modeling using GARCH and DCC models, respectively. The detailed literature could be found in Bollerslev (2008), Engle (2002, 2009).

Even though several strategies are devised to measure capital shortfalls, we directly follow the approach of Brownlees and Engle (2012) to combine balance sheet data with market trading data. Since this approach is market based in spirit, it could also reflect investors' expectations. Our model is introduced as follows. Suppose the financial supervisory institution would restrict each institution to maintain equity as a fraction k of its assets. Thus we can define the capital buffer of the financial institution i at time t as

$$\mathtt{CB}_{it} = W_{it} - k(D_{it} + W_{it}), \quad i = 1, 2, \ldots, I, \tag{1}$$

Where D_{it} and W_{it} are the book value of financial institution's debt and the market value of its equity respectively. When CB_{it} is positive, the financial institution i has sufficient working capital. On the other hand, when CB_{it} is negative, the financial institution i occurs capital shortfall. For convenience, we denote the capital shortfall of the financial institution i at time t as

$$\begin{aligned}\mathtt{CS}_{it} &= -\mathtt{CB}_{it} \\ &= kD_{it} - (1-k)W_{it} \\ &= kD_{it} - (1-k)(1+r_{it})W_{it-1}\end{aligned} \tag{2}$$

Where r_{it} denotes the return of financial institution *i* between period $t - 1$ and *t*.

Note that CS_{it} is combined both accounting and market trading information of a financial institution. Of course, some one may doubt why not directly using the accounting data to measure CS_{it}. The main cause is that the value of assets and liabilities every month or even every quarter. Using instant market trading data can not only quickly expose the systemic risk, but also easily predict its future value. Because a firm's nominal liability (D_{it}) comes due at a future time, in practical applications, we simply measure D_{it} from the recently observable accounting data. However, estimating the market value of equity differs from D_{it}, it can provide a market estimate of the firm's value on the moment. To be more precise, the market value of the financial institution *i* (W_{it}) is estimated through its previous value (W_{it-1}) and an instant estimation of the return (r_{it}). Furthermore, we could take into account some economic factors or use the econometric approach to forecast firm's future market value.

In the works of Brownlees and Engle (2012), they are interested in computing the expected capital shortfall when the financial market is in distress. We agree the importance of expected capital shortfall; nevertheless, the tail behavior of capital shortfall could reveal other useful information. In order to capture the tail behavior of capital shortfall conditional on a market distress, we first denote the capital shortfall conditional on the event $r_{mt} = C_t$ as

$$\mathtt{CS}_{it}|_{r_{mt}=\mathbb{C}_t} = \Big(kD_{it} - (1-k)(1+r_{it})W_{it-1}\Big)\Big|_{r_{mt}=\mathbb{C}_t} \tag{3}$$

Where r_{mt} is the market return at time *t* and C_t is a certain threshold number. Furthermore, we assume that when the market is in distress, debt cannot be renegotiated, implying $D_{it}|r_{mt=Ct} = D_{it}$. Then the Eq. (3) could be rewrite as

$$\mathtt{CS}_{it}|_{r_{mt}=\mathbb{C}_t} = kD_{it} - (1-k)(1+r_{it}|_{r_{mt}=\mathbb{C}_t})W_{it-1}. \tag{4}$$

Recall that Value at Risk (VaR), defined as a worst case scenario in terms of losses on a typical day, is a popular measure of tail risk management that is not only recommended by banking supervisors but is also widely used throughout the financial industry, including by banks and investment funds, see P´erignon and Smith (2010a,b). The value of VaR_{it}^q is implicitly defined as the *q* quantile, i.e.,

$$Pr(r_{it} \leq \mathtt{VaR}_{it}^q) = q. \tag{5}$$

Note that VaR_{it}^q is usually a negative number. In this study, we also focus on a worst-case scenario in terms of the capital shortfall of the institution conditional on the market distress. Then a new tail risk measure CSVaR_{it}^q could be defined as

$$Pr(\mathtt{CS}_{it}|_{r_{mt}=\mathbb{C}_t} \geq \mathtt{CSVaR}^q_{it}) = q. \tag{6}$$

When the financial market is in distress, $\text{CSVaR}_{it}{}^q$ exposes the worst case of capital shortfall. A positive $\text{CSVaR}_{it}{}^q$ means institution *i* may occur capital shortfall. A higher $\text{CSVaR}_{it}{}^q$ implies the financial institution *i* contains higher systemic risk. However, a negative $\text{CSVaR}_{it}{}^q$ indicates that the institution *i* is going to function properly. Therefore, we define the systemic risk index based on the worst capital shortfall of institution *i* as

$$\mathtt{CSRISK}^q_{it} = \max\left(0, \mathtt{CSVaR}^q_{it}\right). \tag{7}$$

Comparing to the general financial institution's stress tests, estimating CSRISK only uses public data and is relatively inexpensive to implement. Then the total amount of systemic risk in the financial system could be defined as

$$\mathtt{CSRISK}^q_{mt} = \sum_{i=1}^{I} \mathtt{CSRISK}^q_{it}. \tag{8}$$

This index shows the whole systemic risk level that provides an early warning system for the government in policy making and for the public in their financial decision making.

3. Estimating CSRISK

In this section, we introduce how to estimate the CSRISK. Although several strategies can be devised to estimate the CSRISK, e.g., developing volatility models or bootstrapping past returns, we adopt the quantile regression approach due to its simplicity and efficiency, see Koenker and Bassett (1978) and Koenker (2005). Although quantile regression estimators seem to be determined by a small subset of observations, in fact, they do not ignore any sample information. Other financial literature using quantile regression approach is included Engle and Manganelli (2004), Boyson et al. (2010), Adams et al. (2010), and Adrian and Brunnermeier (2011).

It is desirable to briefly describe the basic idea of quantile regression approach before moving to our main task. For a random variable *Y* with distribution F_Y , we denote the *q*-th quantile of F_Y as $Q_Y(q)$ which is

$$Q_Y(q) = F^{-1}(q) = \inf\{y : F_Y(y) \geq q\} \tag{9}$$

Where $q \in [0, 1]$. Suppose the *q*-th conditional quantile function is $Q_Y(q|xi)=x'_i\beta_q$. We can estimate β_q by solving

$$\hat{\boldsymbol{\beta}}^q = \operatorname{argmin}_{\boldsymbol{\beta}^q} \sum_{i=1}^{n} \rho^q(y_i - \boldsymbol{x}'_i\boldsymbol{\beta}^q) \tag{10}$$

where $\rho^q(a)=qa$ if $a>0$ and $\rho^q(a)=(q-1)a$ if $a\leq 0$. The quantity $\hat{\beta}^q$ is called the q-th regression quantile. For the case q = 0.5, equation (10) is to minimizes the sum of absolute errors and equally estimate the parameters using the least absolute deviation (LAD) method.

Now we move on to discuss how to estimate CSVaR. By Eqs. (4) and (6), we can find the q-th quantile capital shortfall conditional on r_{mt} as follows,

$$\mathtt{CSVaR}_{it}^{q} = kD_{it} - (1-k)\big(1 + Q_{r_{it}}(q|r_{mt})\big)W_{it-1}, \tag{11}$$

Where $Q_{rit}(q|r_{mt})$ is the q-th quantile of rit conditional on certain value of r_{mt}. Therefore, we just need to estimate $Q_{rit}(q|r_{mt})$, then CSVaR_{it}^{q} can be computed directly. In this study, we use $r_{mt} = \mathrm{VaR}^{0.01}{}_{mt}$ to represent a substantial market decline. Following the idea of Adrian and Brunnermeier (2011), we estimate the conditional distribution as a function of state variable to capture time variation of r_{it} and r_{mt}. We denote M_{t-1} as a vector of lagged state variables and run the following quantile regressions:

$$r_{mt} = \alpha_m + \gamma_m M_{t-1} + \varepsilon_{mt}, \tag{12}$$

$$r_{it} = \alpha_i + \beta_i r_{mt} + \gamma_i M_{t-1} + \varepsilon_{it}. \tag{13}$$

We can obtain the predicted values from above regression as follows,

$$\widehat{\mathtt{VaR}}_{mt}^{0.01} = \hat{\alpha}_m + \hat{\gamma}_m M_{t-1}, \tag{14}$$

$$\widehat{Q}_{r_{it}}(q|r_{mt}) = \hat{\alpha}_i^q + \hat{\beta}_i^q \widehat{\mathtt{VaR}}_{mt}^{0.01} + \hat{\gamma}_i^q M_{t-1}. \tag{15}$$

By Eqs. (11) and (15), the estimation of CSVaR_{it}^{q} is measured as

$$\widehat{\mathtt{CSVaR}}_{it}^{q} = kD_{it} - (1-k)\Big(1 + \hat{\alpha}_i^q + \hat{\beta}_i^q\ \widehat{\mathtt{VaR}}_{mt}^{.01} + \hat{\gamma}_i^q M_{t-1}\Big)W_{it-1}. \tag{16}$$

Note that we assume D_{it} is the newly obtainable data at time $t-1$, thus it does not need to be predicted. Therefore, we can estimate CSRISK_{it}^{q} by

$$\widehat{\mathtt{CSRISK}}_{it}^{q} = \max\big(0, \widehat{\mathtt{CSVaR}}_{it}^{q}\big), \tag{17}$$

and the total amount of systemic risk in the financial system is

$$\widehat{\mathtt{CSRISK}}_{mt}^{q} = \sum_{i=1}^{I} \widehat{\mathtt{CSRISK}}_{it}^{q}. \tag{18}$$

4. Empirical Tests

4.1. Data

In this study, we use the American banks as our sample to verify the feasibility of the CSRISK. The sample period is from 2003/1/1 to 2013/12/31. Weekly returns and market value are extracted from CRSP and the quarterly book value of debt from COMPUSTAT. More clearly, the market value is calculated by prc times cshoq (CRSP codes for the closing price and common shares outstanding). And the book value of debt is measured by dlc pluses dltt (COMPUSTAT codes for financial debt in current liabilities and long-term financial debt). Since market value or debt defined this way should never be negative, so observations with negative market value or debt are deleted from our sample. Furthermore, we also ignore the stocks that contain any missing data in our sample period. For estimating CSRISK, the suitable state variables Mt should be determined. We use the Fama-French three factors including SMB (Small Minus Big), HML (High Minus Low), and the excess return on the market ($R_m - R_f$). All factors data can be downloaded from the French's website. [3]

Based on the above filters, there are 238 banks included in our sample and each stock contains 574 records. Table 1 shows these stocks' tickers and company names. Moreover, we also report the market value, the book value of debt, and the capital buffer on the last trading day (2013/12/27). The size of market value or debt is very important. The bank with bigger market value or debt may have higher probability to induce the market crisis. For example, the market value of BAC is 144,319 millions, but a lot of stocks' market value are less than 100 millions. Maybe we need to pay more attention on the BAC in term of whole market level. The last column in the Table 1 states the capital buffers which are calculated by the Eq. (1). In this study, we always set the capital requirement ratio k is 0.08.

Although only two banks have negative capital buffer value, it does not mean that the financial market is always stable and safety. For more detailed investigating, in the Table 2, we report some basic statistics of the market value, debt, and capital buffer in each year. Take the Panel A as the example. In 2003, based on 238 banks, we first calculate the averages of the market value, debt, and capital buffer in each year. Then, among these averages, their mean, minimum (Min), the first quartile (Q1), median, the third quartile (Q3), and maximum (Max) are 2,876.11, 12.82, 101.83, 262.30, 881.74, and 112,524.38 millions. The most important thing is in the Panel C. In each year, despite most of banks have positive average capital buffer, but some banks face average negative capital buffer or called capital shortfall. Moreover, in this study, we want to find the expected capital shortfall of a bank when the financial market is in distress. Of course, it is natural that each bank usually has larger capital shortfall and we show the results in the following sections.

4.2. Individual CSRISK

The rolling window method is used to determine the 0.01-th quantile of weekly return when market is in distress. In each estimating window, we consider the quantile regression models as Eq. (12) and (13) and let q = 0.01. The estimating period length is fifty, which means that, in each estimating model, fifty weekly returns are used to estimate parameters. After obtaining the 0.01-th quantile of weekly return conditional on market distress, we can determine the individual CSRISK by the Eq.(16) and (17).

[3] French's website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html

We evaluate the downside standard deviations (σ−), the value at risk (VaR), the expected shortfall (ES) and four statistics of CSRISK including median, mean, the third quartile (Q3), and maximum. To show the relation among these risk measures, we make the scatter plots in the Fig 1. It is clear that downside risk (σ−) and VaR (or ES) have strongly liner relationship. However, the relation between the CSRISK and general risk measures is unambiguous. This outcome indicates that although traditional risk measures correspond lots of risk components, but the CSRISK could further provide some omissive information about the systemic risk.

Table 3 reports the results of the top 30 banks in terms of the maximum value of CSRISK from 2004 to 2013. We can find that the size of CSRISK is very various, for instance, the BAC's maximum CSRISK is 70,454 millions, but the CPF's maximum CSRISK is only 70 millions. The government should pay more attention on these banks with large CSRISK. Then we focus only on four banks, JPM, DB, BAC, and KB and plot their boxplots in the Fig. 2. In the Figs. 3-6, we show each bank's market value, weekly returns, book value of debt, capital shortfall, 0.01-th quantile of return conditional on market distress [Q_{rit} (0.01|r=$\mathrm{VaR}^{0.01}{}_{\mathrm{mt}}$)], and CSRISK. We observe that higher CSRISK value usually comes with lower market value, larger debt, and lower Q_{rit} (0.01|r=$\mathrm{VaR}^{0.01}{}_{\mathrm{mt}}$). During the financial crisis of 2008–2009, all banks produce the largest CSRISK.

4.3. Market CSRISK

After determining every bank's individual CSRISK, we can sum them and get the whole market CSRISK as the Eq.(18). The market CSRISK can be regarded as an important index for measuring financial market risk, because it represents expect value of the worst market capital shortfall conditional on market distress. In the Table 4, we divide full sample period into 10 years and calculate the mean, minimum, maximum, and five different quantiles (10%, 30%, 50%, 70%, 90%) of the market CSRISK. Since the financial crisis happened in the end of 2008, thus the market CSRISK exhibits the largest value in 2009 in terms of mean and maximum. In the Figure 7, we plot the maximum market CSRISK in each year. It clearly indicates that the CSRISK is increasing from 2004 to 2009 and then is slightly decreasing. However, we need to note that although the maximum of CSRISK is decreasing from 2011 to 2013, but its mean keeps about 70,000 millions and its minimum is sharply increasing in 2013.

5. Conclusions

In this project, we propose a new measure for systemic risk and name it as CSRISK index that expresses the worst capital shortfall of a financial institution conditional on a substantial market decline. This index only needs public financial data including accounting and market trading information, thus it is quick and inexpensive. Furthermore, the sum of all institutions' CSRISKs in the whole financial system represents an early warning indicator for the banking supervisor. The quantile regression approach is introduced to estimate the CSRISK. We use 238 U.S. banks from 2003 to 2013 as the empirical sample. Although traditional risk measures correspond lots of risk components, but the empirical results indicate that the CSRISK can provide some omissive information. Besides, all banks indeed produce the largest CSRISK during the financial crisis of 2008–2009. In terms of the market CSRISK, we find it is increasing from 2004 to 2009 and then is slightly decreasing. This systemic risk measure can potentially be widely applied in the practical risk management and macroprudential policy making.

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Table 1: Data Descriptions: Market Value, Debt, and Capital Buffer

Num	Ticker	Company Name	Marekt Value ($m)	Debt ($m)	Capital Buffer ($m)
1	ABCB	AMERIS BANCORP	404	85	365
2	AF	ASTORIA FINANCIAL CORP	1,123	4,033	711
3	AMNB	AMERICAN NATL BANKSHARES	176	81	156
4	AMRB	AMERICAN RIVER BANKSHARES	73	17	66
5	AROW	ARROW FINANCIAL CORP	309	77	278
6	ASBC	ASSOCIATED BANC-CORP	2,610	2,846	2,174
7	ASBI	AMERIANA BANCORP	32	46	26
8	ASRV	AMERISERV FINANCIAL INC/PA	58	57	48
9	AUBN	AUBURN NATIONAL BANCORP	83	30	74
10	BAC	BANK OF AMERICA CORP	144,319	538,337	89,706
11	BANF	BANCFIRST CORP/OK	735	41	673
12	BANR	BANNER CORP	683	187	613
13	BAP	CREDICORP LTD	11,042	8,396	9,487
14	BBT	BB&T CORP	23,284	23,462	19,544
15	BBX	BBX CAPITAL CORP	186	155	158
16	BCH	BANCO DE CHILE	14,118	10,519	12,147
17	BCS	BARCLAYS PLC	58,730	571,066	8,346
18	BCSB	BCSB BANCORP INC	67	17	60
19	BFR	BBVA BANCO FRANCES SA	949	10	872
20	BHB	BAR HARBOR BANKSHARES	144	368	103
21	BK	BANK OF NEW YORK MELLON CORP	34,485	31,045	29,242
22	BKMU	BANK MUTUAL CORP	275	210	236
23	BKSC	BANK SOUTH CAROLINA CORP	59	-	55
24	BLX	BANCO LATINOAMERICANO DE COM	945	3,599	582
25	BMO	BANK OF MONTREAL	41,190	67,558	32,490
26	BMRC	BANK OF MARIN BANCORP	225	23	205
27	BMTC	BRYN MAWR BANK CORP	342	229	296
28	BNS	BANK OF NOVA SCOTIA	69,445	113,577	54,803
29	BOH	BANK OF HAWAII CORP	2,339	1,022	2,070
30	BOKF	BOK FINANCIAL CORP	4,323	3,988	3,658
31	BPFH	BOSTON PRIVATE FINL HOLDINGS	836	662	716
32	BPOP	POPULAR INC	2,947	4,499	2,351
33	BRKL	BROOKLINE BANCORP INC	635	826	519
34	BSRR	SIERRA BANCORP/CA	209	36	189
35	BUSE	FIRST BUSEY CORP	423	205	372
36	BXS	BANCORPSOUTH INC	1,772	551	1,586
37	BYFC	BROADWAY FINANCIAL CORP/DE	5	92	-3
38	CAC	CAMDEN NATIONAL CORP	284	399	230
39	CACB	CASCADE BANCORP	285	33	259
40	CAFI	CAMCO FINANCIAL CORP	57	62	48
41	CASH	META FINANCIAL GROUP INC	167	118	144
42	CATY	CATHAY GENERAL BANCORP	1,743	1,366	1,494
43	CBAN	COLONY BANKCORP INC	52	64	43
44	CBIN	COMMUNITY BK SHARES INC/IN	59	90	47
45	CBSH	COMMERCE BANCSHARES INC	3,899	1,629	3,456
46	CBU	COMMUNITY BANK SYSTEM INC	1,295	505	1,151
47	CCBG	CAPITAL CITY BK GROUP INC	206	153	177
48	CCNE	CNB FINANCIAL CORP/PA	223	122	195
49	CFFI	C&F FINANCIAL CORP	158	167	132
50	CFFN	CAPITOL FEDERAL FINL INC	1,758	2,911	1,385
51	CFNL	CARDINAL FINANCIAL CORP	500	372	430
52	CFR	CULLEN/FROST BANKERS INC	3,958	786	3,578
53	CHCO	CITY HOLDING CO	653	149	589
54	CHFC	CHEMICAL FINANCIAL CORP	778	349	688
55	CLBH	CAROLINA BANK HOLDINGS INC	37	26	32
56	CMA	COMERICA INC	7,299	4,014	6,394
57	CNBKA	CENTURY BANCORP INC/MA	188	440	137
58	COBZ	COBIZ FINANCIAL INC	373	287	320
59	COLB	COLUMBIA BANKING SYSTEM INC	1,134	100	1,035
60	CPF	CENTRAL PACIFIC FINANCIAL CP	736	117	668
61	CSFL	CENTERSTATE BANKS INC	280	85	251
62	CTBI	COMMUNITY TRUST BANCORP INC	594	298	522
63	CVBF	CVB FINANCIAL CORP	1,332	781	1,163
64	CVLY	CODORUS VALLEY BANCORP	80	73	68
65	CWBC	COMMUNITY WEST BANCSHARES	38	37	32
66	CYN	CITY NATIONAL CORP	3,458	916	3,108
67	DB	DEUTSCHE BANK AG	45,798	328,278	15,872
68	DCOM	DIME COMMUNITY BANCSHARES	564	836	452
69	EGBN	EAGLE BANCORP INC/MD	632	129	571
70	ESBF	ESB FINANCIAL CORP	222	471	167
71	ESBK	ELMIRA SVGS BANK ELMIRA/NY	57	57	48
72	EVBN	EVANS BANCORP INC	78	35	69
73	EVBS	EASTERN VA BANKSHARES INC	60	104	47
74	EWBC	EAST WEST BANCORP INC	3,928	1,471	3,496
75	FBC	FLAGSTAR BANCORP INC	861	3,089	545

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Table 1 (continued from previous page)

Num	Ticker	Company Name	Marekt Value ($m)	Debt ($m)	Capital Buffer ($m)
76	FBMI	FIRSTBANK CORP	125	104	106
77	FBNC	FIRST BANCORP/NC	282	46	255
78	FBP	FIRST BANCORP P R	1,274	1,489	1,052
79	FBSS	FAUQUIER BANKSHARES INC	47	21	42
80	FCBC	FIRST CMNTY BANCSHARES INC	318	286	269
81	FCCY	1ST CONSTITUTION BANCORP	58	29	51
82	FCF	FIRST COMMONWLTH FINL CP/PA	745	693	630
83	FCNCA	FIRST CITIZENS BANCSH -CL A	1,907	1,054	1,670
84	FCZA	FIRST CITIZENS BANC CORP	52	89	41
85	FDEF	FIRST DEFIANCE FINANCIAL CP	235	120	207
86	FFBC	FIRST FINL BANCORP INC/OH	904	703	775
87	FFIC	FLUSHING FINANCIAL CORP	534	994	411
88	FFIN	FIRST FINL BANKSHARES INC	1,731	404	1,560
89	FFKT	FARMERS CAPITAL BANK CORP	150	206	121
90	FFKY	FIRST FINANCIAL SERVICE CORP	18	43	13
91	FISI	FINANCIAL INSTITUTIONS INC	287	189	249
92	FITB	FIFTH THIRD BANCORP	15,721	10,911	13,590
93	FLIC	FIRST LONG ISLAND CORP	313	301	264
94	FMBI	FIRST MIDWEST BANCORP INC	1,092	420	971
95	FMER	FIRSTMERIT CORP	2,992	1,402	2,641
96	FNFG	FIRST NIAGARA FINANCIAL GRP	3,437	4,488	2,803
97	FNLC	FIRST BANCORP INC/ME	183	263	147
98	FRBK	REPUBLIC FIRST BANCORP INC	77	22	69
99	FRME	FIRST MERCHANTS CORP	512	452	435
100	FSBK	FIRST SOUTH BANCORP INC/VA	63	10	57
101	FULT	FULTON FINANCIAL CORP	2,281	2,212	1,922
102	FUNC	FIRST UNITED CORP	50	233	27
103	GABC	GERMAN AMERICAN BANCORP INC	307	163	269
104	GBCI	GLACIER BANCORP INC	1,627	1,442	1,382
105	GCBC	GREENE COUNTY BANCORP INC	97	11	88
106	GFED	GUARANTY FED BANCSHARES INC	29	82	20
107	GGAL	GRUPO FINANCIERO GALICIA SA	908	1,534	713
108	GLBZ	GLEN BURNIE BANCORP	33	21	28
109	GSBC	GREAT SOUTHERN BANCORP	367	380	308
110	HAFC	HANMI FINANCIAL CORP	542	25	497
111	HBAN	HUNTINGTON BANCSHARES	6,676	2,920	5,909
112	HBHC	HANCOCK HOLDING CO	2,613	1,157	2,311
113	HBNC	HORIZON BANCORP/IN	186	281	149
114	HCBK	HUDSON CITY BANCORP INC	4,724	12,175	3,372
115	HFBC	HOPFED BANCORP INC	80	102	66
116	HFFC	HF FINANCIAL CORP	93	163	72
117	HFWA	HERITAGE FINANCIAL CORP	237	18	217
118	HIFS	HINGHAM INSTN FOR SAVINGS	148	269	115
119	HMNF	HMN FINANCIAL INC	32	18	28
120	HTBK	HERITAGE COMMERCE CORP	189	5	173
121	IBCA	INTERVEST BANCSHARES CORP	141	59	125
122	IBCP	INDEPENDENT BANK CORP/MI	132	67	116
123	IBKC	IBERIABANK CORP	1,607	602	1,431
124	IBOC	INTL BANCSHARES CORP	1,487	2,093	1,201
125	INDB	INDEPENDENT BANK CORP/MA	787	530	682
126	IRE	BANK OF IRELAND	903	16,052	-453
127	JPM	JPMORGAN CHASE & CO	195,845	587,964	133,140
128	KB	KB FINANCIAL GROUP	13,261	34,703	9,424
129	KEY	KEYCORP	10,107	8,871	8,589
130	LARK	LANDMARK BANCORP INC/KS	60	63	50
131	LBAI	LAKELAND BANCORP INC	369	229	321
132	LION	FIDELITY SOUTHERN CORP	267	187	231
133	LKFN	LAKELAND FINANCIAL CORP	494	207	438
134	LNBB	LNB BANCORP INC	83	65	71
135	LSBI	LSB FINANCIAL CORP	38	10	34
136	LYG	LLOYDS BANKING GROUP PLC	72,558	216,496	49,434
137	MBFI	MB FINANCIAL INC/MD	1,467	468	1,312
138	MBRG	MIDDLEBURG FINANCIAL CORP	135	128	114
139	MBVT	MERCHANTS BANCSHARES INC/VT	187	229	154
140	MBWM	MERCANTILE BANK CORP	164	138	140
141	MCBC	MACATAWA BANK CORP	139	133	117
142	MFSF	MUTUALFIRST FINANCIAL INC	107	108	89
143	MSFG	MAINSOURCE FINL GROUP INC	298	270	253
144	MSL	MIDSOUTH BANCORP INC	178	137	153
145	MTB	M & T BANK CORP	14,168	5,488	12,596
146	NASB	NASB FINANCIAL INC	199	151	171
147	NBTB	N B T BANCORP INC	965	777	826
148	NHTB	NEW HAMPSHIRE THRIFT BNCSHRS	99	170	78
149	NKSH	NATIONAL BANKSHARES INC VA	246	-	226
150	NOVB	NORTH VALLEY BANCORP	122	29	110
151	NPBC	NATIONAL PENN BANCSHARES INC	1,503	949	1,307

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Table 1 (continued from previous page)

Num	Ticker	Company Name	Marekt Value ($m)	Debt ($m)	Capital Buffer ($m)
152	NRIM	NORTHRIM BANCORP INC	153	45	138
153	NTRS	NORTHERN TRUST CORP	13,411	7,468	11,741
154	OCFC	OCEANFIRST FINANCIAL CORP	276	321	228
155	OCN	OCWEN FINANCIAL CORP	6,268	4,175	5,433
156	OFG	OFG BANCORP	752	1,822	546
157	OKSB	SOUTHWEST BANCORP INC	280	142	246
158	ONB	OLD NATIONAL BANCORP	1,405	1,201	1,197
159	OPOF	OLD POINT FINANCIAL CORP	63	56	54
160	OSBC	OLD SECOND BANCORP INC/IL	63	147	46
161	OZRK	BANK OF THE OZARKS INC	1,624	419	1,460
162	PBCT	PEOPLE'S UNITED FINL INC	4,358	4,184	3,675
163	PCBK	PACIFIC CONTINENTAL CORP	219	172	188
164	PEBK	PEOPLES BANCORP NC INC	69	135	53
165	PEBO	PEOPLES BANCORP INC/OH	230	209	195
166	PFBI	PREMIER FINANCIAL BANCORP	98	29	88
167	PFBX	PEOPLES FINANCIAL CORP/MS	63	207	41
168	PGC	PEAPACK-GLADSTONE FINL CORP	154	53	137
169	PKBK	PARKE BANCORP INC	47	44	40
170	PMBC	PACIFIC MERCANTILE BANCORP	115	75	100
171	PNBK	PATRIOT NATIONAL BANCORP INC	53	53	44
172	PNC	PNC FINANCIAL SVCS GROUP INC	37,583	39,931	31,382
173	PNFP	PINNACLE FINL PARTNERS INC	938	410	830
174	PPBI	PACIFIC PREMIER BANCORP INC	210	83	186
175	PRK	PARK NATIONAL CORP	1,140	1,122	959
176	PROV	PROVIDENT FINANCIAL HOLDINGS	175	118	151
177	PULB	PULASKI FINANCIAL CORP	113	132	94
178	PVTB	PRIVATEBANCORP INC	1,669	684	1,481
179	PWOD	PENNS WOODS BANCORP INC	204	95	180
180	QCRH	QCR HOLDINGS INC	93	554	41
181	RBCAA	REPUBLIC BANCORP INC/KY	497	749	398
182	RBPAA	ROYAL BANCSHARES/PA -CL A	19	135	7
183	RF	REGIONS FINANCIAL CORP	12,561	7,602	10,948
184	RIVR	RIVER VALLEY BANCORP	35	53	28
185	RY	ROYAL BANK OF CANADA	90,154	124,682	72,967
186	SAL	SALISBURY BANCORP INC	45	34	38
187	SASR	SANDY SPRING BANCORP INC	567	593	474
188	SBCF	SEACOAST BANKING CORP/FL	199	255	163
189	SBSI	SOUTHSIDE BANCSHARES INC	425	657	339
190	SHBI	SHORE BANCSHARES INC	64	11	58
191	SIVB	SVB FINANCIAL GROUP	3,693	462	3,361
192	SNBC	SUN BANCORP INC/NJ	298	162	261
193	SRCE	1ST SOURCE CORP	637	315	561
194	STBA	S & T BANCORP INC	634	259	563
195	STI	SUNTRUST BANKS INC	17,260	17,222	14,502
196	STSA	STERLING FINANCIAL CORP/WA	1,578	1,747	1,312
197	STT	STATE STREET CORP	28,717	22,443	24,624
198	SUBK	SUFFOLK BANCORP	194	-	178
199	SUSQ	SUSQUEHANNA BANCSHARES INC	2,304	2,497	1,920
200	SVBI	SEVERN BANCORP INC	48	139	33
201	TAYC	TAYLOR CAPITAL GROUP INC	572	1,494	407
202	TCB	TCF FINANCIAL CORP	2,408	1,713	2,079
203	TCBK	TRICO BANCSHARES	337	51	306
204	TD	TORONTO DOMINION BANK	78,167	83,712	65,217
205	THFF	FIRST FINANCIAL CORP/IN	426	156	379
206	THRD	TF FINANCIAL CORP	77	52	67
207	TMP	TOMPKINS FINANCIAL CORP	645	461	556
208	TOFC	TOWER FINANCIAL CORP	79	34	70
209	TRMK	TRUSTMARK CORP	1,710	501	1,533
210	TRST	TRUSTCO BANK CORP/NY	557	180	498
211	TSBK	TIMBERLAND BANCORP INC	58	45	50
212	TSH	TECHE HOLDING CO	89	107	73
213	UBFO	UNITED SECURITY BANCSHARS CA	62	11	56
214	UBOH	UNITED BANCSHARES INC/OH	43	31	37
215	UBSI	UNITED BANKSHARES INC/WV	1,399	774	1,225
216	UCBI	UNITED COMMUNITY BANKS INC	781	213	702
217	UCFC	UNITED COMMUNITY FINL CORP	187	141	161
218	UMBF	UMB FINANCIAL CORP	2,304	1,776	1,978
219	UMPQ	UMPQUA HOLDINGS CORP	1,686	626	1,501
220	UNB	UNION BANKSHARES INC	94	16	85
221	UNTY	UNITY BANCORP INC	53	104	41
222	USB	U S BANCORP	66,132	47,299	57,058
223	USBI	UNITED SEC BANCSHARES INC	49	3	45
224	VCBI	VIRGINIA COMM BANCORP INC	481	405	410
225	VLY	VALLEY NATIONAL BANCORP	1,971	3,074	1,567
226	WABC	WESTAMERICA BANCORPORATION	1,278	108	1,167
227	WASH	WASHINGTON TR BANCORP INC	496	355	428

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Table 1 (continued from previous page)

Num	Ticker	Company Name	Marekt Value ($m)	Debt ($m)	Capital Buffer ($m)
228	WBCO	WASHINGTON BANKING CO	228	26	208
229	WBK	WESTPAC BANKING	36,310	63,800	28,301
230	WBS	WEBSTER FINANCIAL CORP	2,282	3,183	1,845
231	WFC	WELLS FARGO & CO	212,748	192,581	180,321
232	WFD	WESTFIELD FINANCIAL INC	154	328	115
233	WSBC	WESBANCO INC	790	317	701
234	WSFS	WSFS FINANCIAL CORP	503	859	394
235	WTBA	WEST BANCORPORATION INC	204	182	173
236	WTFC	WINTRUST FINANCIAL CORP	1,556	982	1,353
237	WVFC	WVS FINANCIAL CORP	23	99	13
238	ZION	ZIONS BANCORPORATION	5,005	2,558	4,400

Table 2: Market Value, Debt, and Capital Buffer

We first calculate the averages of the market value, debt, and capital buffer in each year.Then, among the averages of these three variables, we report their mean, minimum (Min), the first quartile (Q_1), median, the third quartile (Q_3), and maximum (Max) in this table.

	Mean ($m)	Min ($m)	Q_1 ($m)	Median ($m)	Q_3 ($m)	Max ($m)
Panel A: Market Value						
2003	2,876.11	12.82	101.83	262.30	881.74	112,524.38
2004	3,778.44	4.04	122.66	334.33	1,093.90	174,433.94
2005	4,114.53	17.15	135.26	349.37	1,278.53	180,433.90
2006	4,965.87	11.88	146.91	397.67	1,386.78	224,612.71
2007	5,338.12	17.63	134.22	354.31	1,345.62	219,599.04
2008	4,276.53	1.64	89.39	266.69	1,037.06	141,950.14
2009	3,880.01	7.68	62.26	193.23	832.32	138,606.66
2010	4,997.21	3.23	63.11	239.48	1,116.39	159,402.31
2011	4,998.29	3.59	69.98	231.80	1,141.97	152,912.11
2012	5,093.62	2.25	80.75	279.09	1,283.30	173,967.27
2013	6,426.44	4.92	122.41	367.94	1,599.89	212,747.61
Panel B: Book Value of Debt						
2003	5,789.76	0.00	62.02	194.10	848.23	277,420.81
2004	6,565.05	0.00	95.86	257.19	874.96	290,592.66
2005	8,350.79	0.00	103.70	275.46	1,044.80	408,380.90
2006	9,974.93	0.08	121.63	279.16	1,159.54	508,622.08
2007	12,722.06	0.00	110.16	296.77	1,288.21	719,825.23
2008	13,471.32	0.00	145.79	397.65	1,554.25	623,357.71
2009	14,519.47	0.00	126.78	352.52	1,322.42	806,691.72
2010	14,178.82	0.00	111.35	279.77	1,167.68	848,792.17
2011	14,643.02	0.00	90.00	241.30	1,197.98	704,466.79
2012	14,274.38	0.00	79.51	249.94	1,135.39	620,407.08
2013	13,935.55	0.00	82.44	231.10	1,104.69	587,963.94
Panel C: Capital Buffer						
2003	2,182.84	-19,088.14	88.62	218.35	736.67	88,015.10
2004	2,950.96	-18,735.45	100.12	278.72	926.17	137,231.81
2005	3,117.30	-22,821.23	110.60	279.30	1,002.18	133,328.71
2006	3,770.61	-10,230.29	114.92	303.75	1,118.30	165,953.93
2007	3,893.30	-15,624.68	104.60	277.79	1,068.57	156,265.80
2008	2,856.70	-3,778.48	58.39	195.59	778.43	83,468.48
2009	2,408.05	-9,867.10	33.06	132.90	603.83	78,335.62
2010	3,463.13	-137.18	46.00	182.98	897.10	117,502.76
2011	3,426.98	-2,490.87	51.47	194.51	927.19	120,743.18
2012	3,544.18	-1,710.67	64.52	228.94	1,078.76	145,504.84
2013	4,797.48	-453.15	100.76	306.63	1,374.66	180,321.28

Table 3: Top 30 Banks with the Highest CSRISK

We evaluate the downside standard deviations (σ^-), the value at risk (VaR), the expected shortfall (ES) and four statistics of CSRISK including median, mean, the third quartile (Q_3), and maximum. The Table 3 reports the results of the top three banks interns of the maximum value of CSRISK from 2004 to 2013.

	General Risk Measures					CSRISK ($m)			
Ticker	σ^-	VaR (99%)	ES (99%)	VaR (97.5%)	ES (97.5%)	Median	Mean	Quartile 3	Maximum
BAC	0.0535	-0.2237	-0.3920	-0.1108	-0.2469	0.0	3149.6	0.0	70454.3
BCS	0.0636	-0.2115	-0.4396	-0.1437	-0.2811	8961.6	21439.3	45611.3	52932.6
LYG	0.0652	-0.2791	-0.4526	-0.1690	-0.3083	6364.4	11546.4	21202.7	35870.2
DB	0.0446	-0.2004	-0.2541	-0.1209	-0.1958	0.0	2043.6	0.0	32476.6
JPM	0.0378	-0.1219	-0.2388	-0.0958	-0.1586	0.0	289.7	0.0	25859.6
WBK	0.0360	-0.1329	-0.2183	-0.0902	-0.1532	0.0	3291.1	6729.1	13431.7
IRE	0.0828	-0.3802	-0.5056	-0.2790	-0.3906	0.0	2503.0	5306.7	8917.3
WFC	0.0397	-0.1817	-0.2795	-0.1012	-0.1892	0.0	8.2	0.0	4270.2
KB	0.0453	-0.1650	-0.2297	-0.1291	-0.1773	1487.1	1199.6	1773.6	3519.8
STT	0.0444	-0.1534	-0.2945	-0.1096	-0.1931	0.0	18.3	0.0	2255.2
FITB	0.0639	-0.2671	-0.4652	-0.1620	-0.3188	0.0	42.6	0.0	1885.2
RF	0.0526	-0.2437	-0.3102	-0.1730	-0.2402	0.0	10.3	0.0	1129.7
KEY	0.0520	-0.1839	-0.3564	-0.1471	-0.2422	0.0	9.6	0.0	1076.0
STI	0.0505	-0.2490	-0.3322	-0.1571	-0.2397	0.0	6.3	0.0	986.5
BCH	0.0446	-0.1732	-0.3392	-0.0951	-0.2090	418.4	440.6	544.9	752.7
BPOP	0.0521	-0.2038	-0.2843	-0.1585	-0.2243	0.0	9.8	0.0	459.7
FBC	0.0837	-0.3544	-0.5407	-0.2349	-0.3850	0.0	74.0	113.4	443.6
FBP	0.0680	-0.2788	-0.3632	-0.2243	-0.2958	0.0	45.6	68.5	376.2
OFG	0.0635	-0.3012	-0.4911	-0.1436	-0.3100	0.0	39.8	32.0	332.6
HBAN	0.0518	-0.2449	-0.3475	-0.1538	-0.2539	0.0	3.0	0.0	329.2
STSA	0.0849	-0.3858	-0.5343	-0.2824	-0.4115	0.0	33.2	0.0	256.9
WBS	0.0525	-0.2392	-0.3752	-0.1110	-0.2468	0.0	6.6	0.0	222.7
GGAL	0.0520	-0.1756	-0.3029	-0.1293	-0.2090	0.0	29.7	36.7	222.3
COLB	0.0489	-0.1885	-0.3433	-0.1161	-0.2241	0.0	1.3	0.0	171.3
BBX	0.0853	-0.3936	-0.4778	-0.2730	-0.3887	0.0	16.7	6.1	162.3
EWBC	0.0508	-0.2013	-0.3120	-0.1332	-0.2209	0.0	1.2	0.0	131.8
AF	0.0348	-0.1405	-0.1848	-0.0985	-0.1419	0.0	0.6	0.0	105.0
CMA	0.0397	-0.1786	-0.2286	-0.1219	-0.1765	0.0	0.2	0.0	101.6
BLX	0.0369	-0.1574	-0.2245	-0.0996	-0.1632	0.0	0.7	0.0	82.9
CPF	0.0697	-0.3212	-0.4510	-0.1956	-0.3283	0.0	6.3	0.0	70.5

Table 4: Market CSRISK Summary

We divide full sample period into 10 years and calculate the mean, minimum, maximum, and five different quantiles (10%, 30%, 50%, 70%, 90%) of the market. CSRISK.

Year	mean	minimum	10%	30%	50%	70%	90%	maximum
2004	6,702	400	413	437	477	13,684	13,804	22,194
2005	19,217	294	296	357	425	43,853	44,096	44,333
2006	22,722	248	268	281	308	52,363	52,593	59,606
2007	31,171	271	321	2,279	11,163	68,891	69,498	76,977
2008	41,092	1,880	2,660	6,261	35,880	71,012	80,653	108,713
2009	85,159	10,501	10,762	25,278	96,837	120,630	147,933	180,621
2010	45,505	2,368	2,550	2,872	3,465	98,304	98,897	103,966
2011	68,134	33,232	34,638	36,255	41,617	108,410	108,744	109,238
2012	71,952	27,970	28,041	72,261	77,247	92,679	99,194	103,272
2013	70,492	61,964	62,175	62,319	67,003	80,794	81,013	84,582
Full-Period	46,289	248	356	7,425	43,791	71,385	102,092	180,621

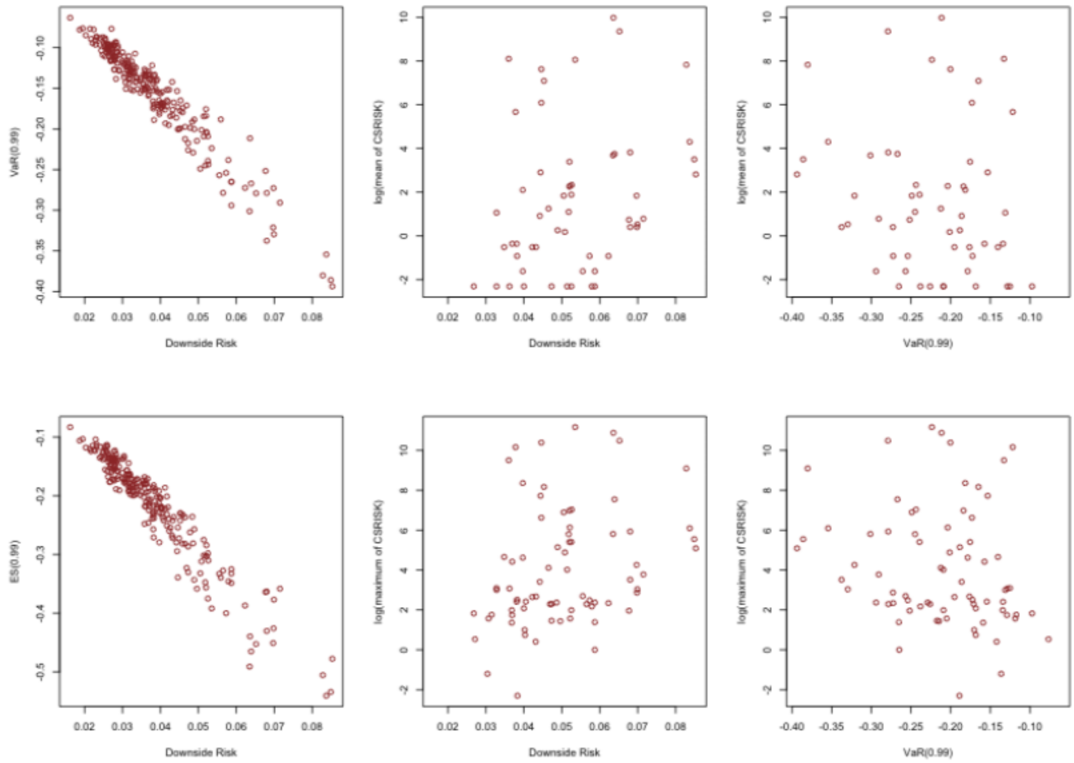

Figure 1: General Risk Measures and CSRISK

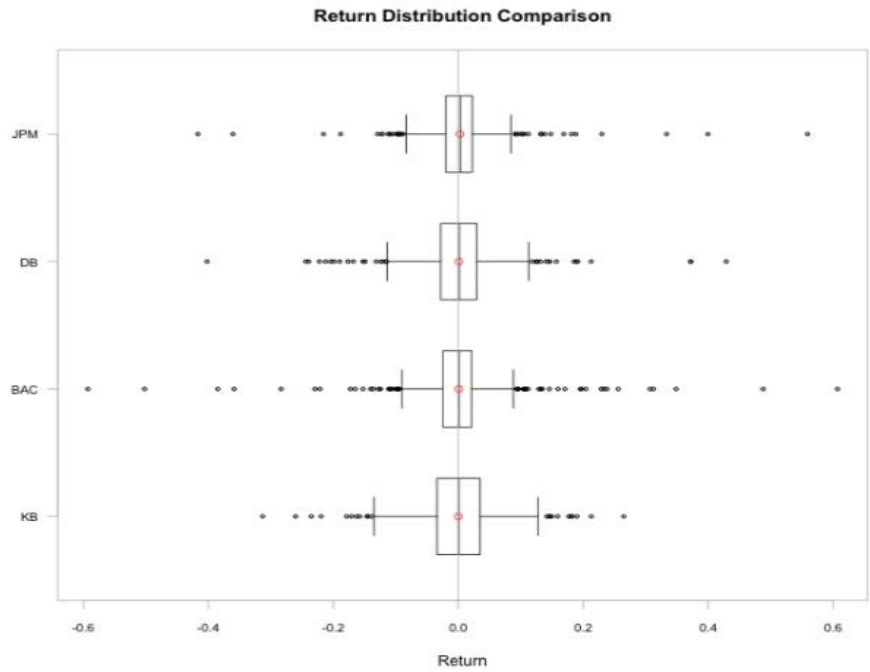

Figure 2: BoxPlots of JPM, DB, BAC, and KB from 2003 to 2013

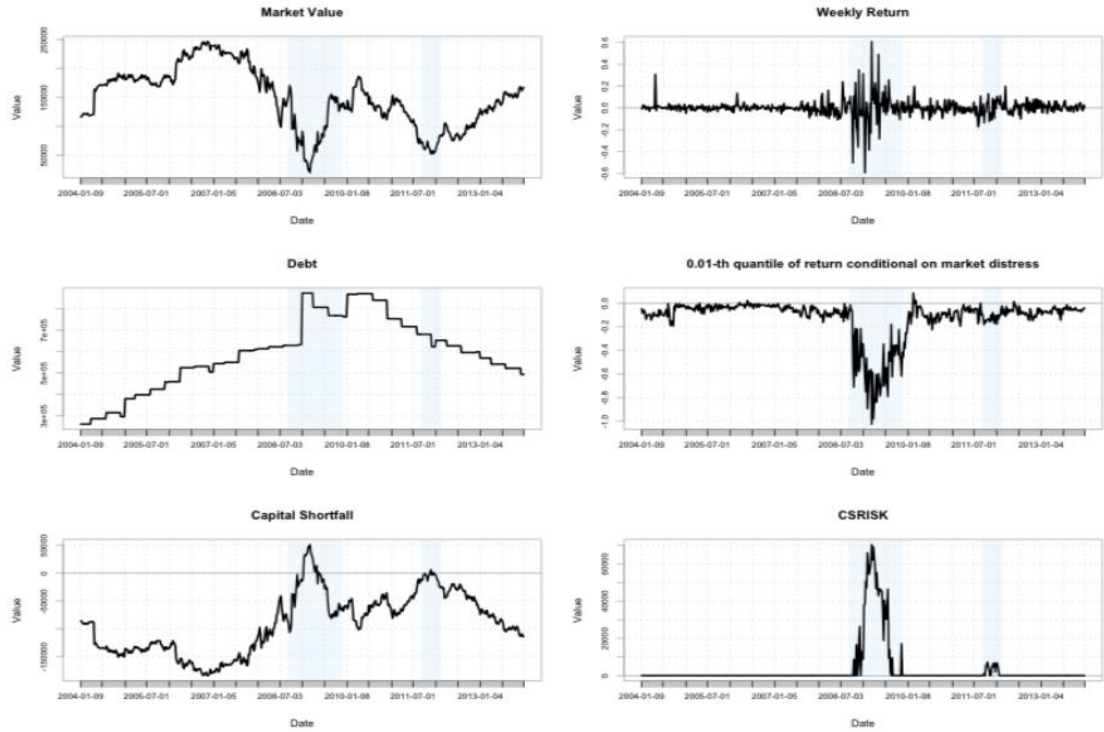

Figure 3: BAC: Individual CSRISK and Other Related Variables

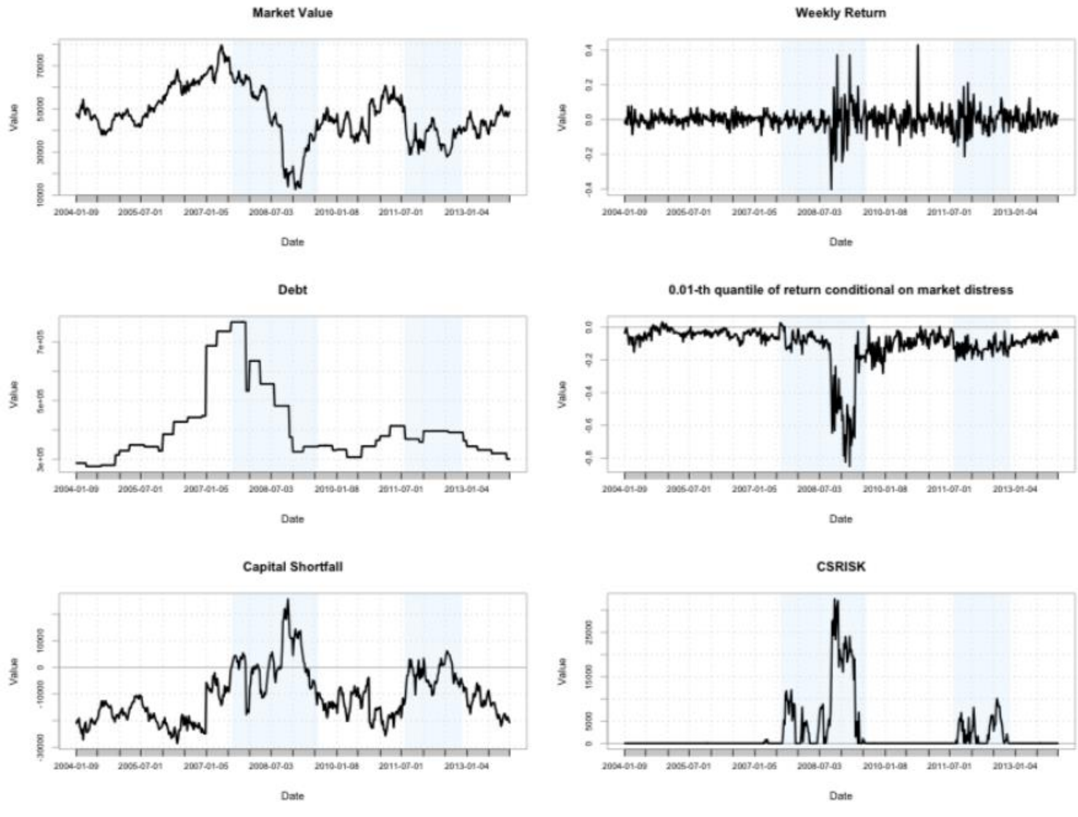

Figure 4: DB: Individual CSRISK and Other Related Variables

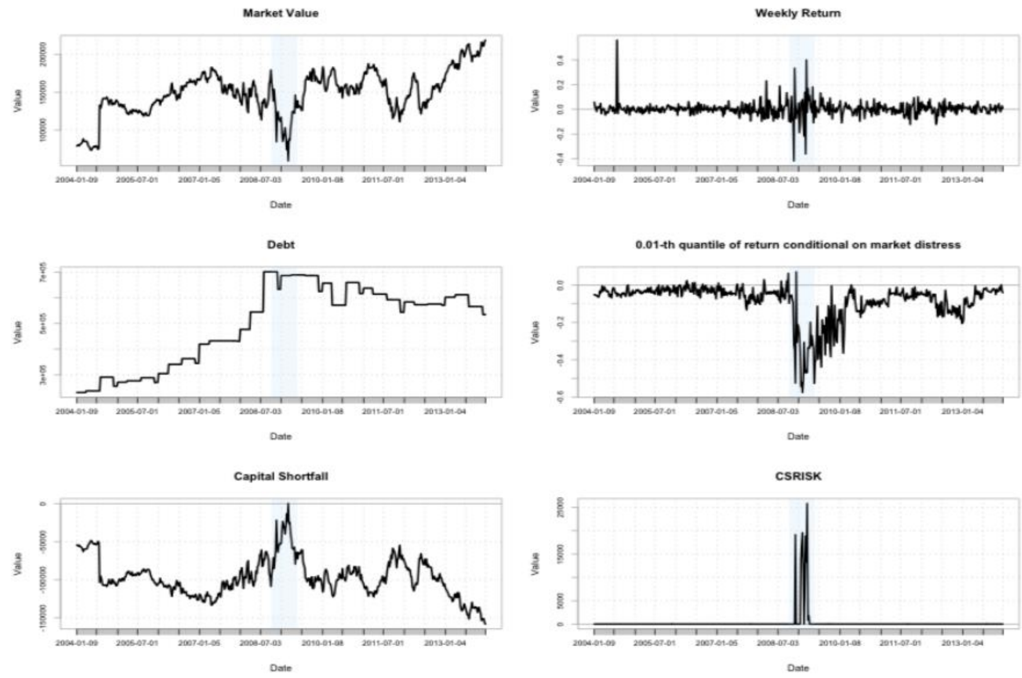

Figure 5: JPM: Individual CSRISK and Other Related Variables

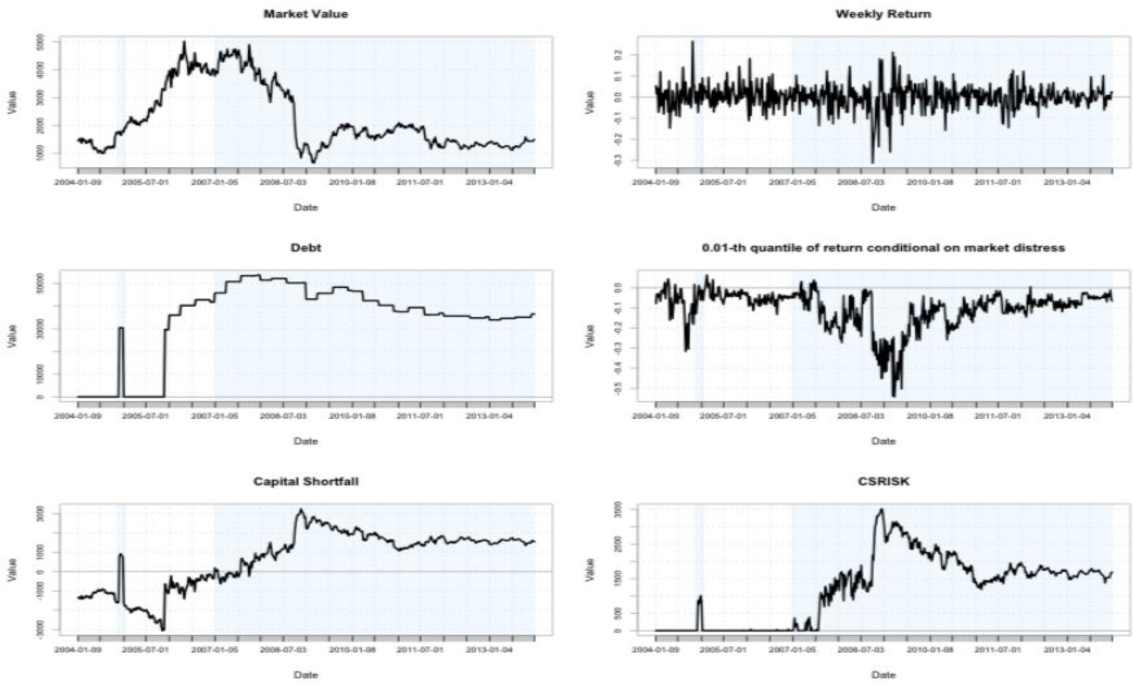

Figure 6: KB: Individual CSRISK and Other Related Variables

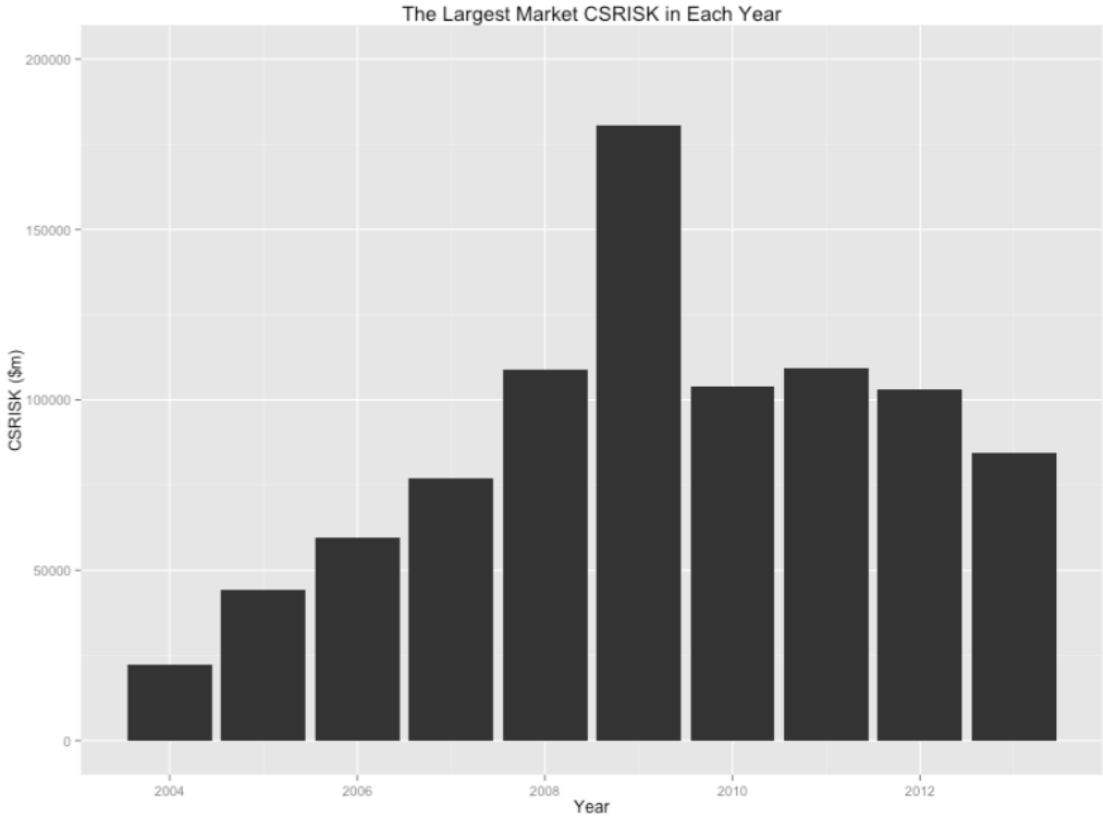

Figure 7: Market CSRISK from 2004 to 2013