Systemic Risk in the Banking Industry of the United States

Weiyu Gao

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By: **Weiyu Gao**

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Signed by the final examining committee:

____________________ Chair
Dr. Harjeet S. Bhabra Examiner

Dr. Rahul Ravi Examiner

Dr. Latha Shanker Supervisor

Approved by

Chair of Department or Graduate Program Director
Dr. Harjeet S. Bhabra

Dean of Faculty
Dr. Harjeet S. Bhabra

Date

September 5th, 2013

Abstract

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In this thesis, I estimate the systemic risk in the U.S. banking industry and the effects of a financial regulation and an event on the financial health and stability of U. S. banks. The financial regulation and event are respectively Basel I and the U.S. sub-prime mortgage financial crisis which are captured by two dummy variables. I estimate systemic risk using the definition which considers a systemic crisis as an event causing a simultaneous default of a significant number of financial institutions. Thus, the systemic risk here is the simultaneous probability of default of a certain number of financial institutions. Next, I form two systemic risk indices, including the default probability based on bank assets and the default probability based on the number of banks. I investigate the sources of systemic risk and address the factors which are significantly related to the stability of the banking system. In order to conduct this investigation, I establish two categories of variables related to systemic factors and bank specific factors. The systemic factors include the median correlation of assets, volatility of assets and capitalization while the bank specific factors consist of time trend, bank size and the ratio of book value of equity to total assets. The regression analyses are applied between the systemic risk indices and the systemic/ bank specific factors. The results suggest that Basel I does not effectively improve the stability of the banking system and that the financial crisis contributes to systemic risk. The volatility of assets and capitalization are significantly related to the systemic risk indices. Although the systemic factors perform better than the bank specific factors in explaining the systemic risk indices, bank size is also a significant explanatory factor.

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Chapter 1. Introduction

In the light of multiple financial crises in the past three decades, issues on financial stability have gained renewed prominence in the literature in recent years. The worldwide financial crisis which began in 2007 has simulated a new examination of the source and transmission of risk in the financial sector and its mechanism for affecting the financial system. Since the default of Lehman Brothers in the autumn of 2008, the term “systemic risk” has become very topical and literally attracted the attention of many financial researchers.

There is still a widespread confusion with regards to the definition of systemic risk and the precise definition, in the words of Schwarcz (2008), remains somewhat unsettled. Bandt and Hartmann (2000) first identify a systemic event as a release of negative information associated with the failure of a financial institution or collapse of a financial market which may conduct a chain of adverse effects upon other institutions or markets. Next, they define systemic risk as a significant probability of a default of the entire financial system. Schwarcz (2008) summarized previous works and concludes that a common factor in these various definitions of systemic risk is a trigger event that can be an economic shock or institutional failure which induces a chain of negative economic consequences, also referred to as a domino effect.

The development of financial engineering and communication technologies has significantly transformed the entire financial environment. One of the most important consequences of this change is the acceleration of financial sector integration. Due to the increase in the correlation of the financial market, each financial institution cannot be treated on an individual basis. Any single failure has the potential to simulate a domino effect and cause a subsequent contagion, which is defined by Gleeson, Hurd, Melnik, and Hackett (2011) as the spread of failures through a financial system, within which any successive default will increase pressure on the remaining components of the system. Furfine (2012) classifies systemic risk into two types. The first is the risk that a financial shock induces a simultaneous default of a set of financial institutions. The second is the risk that the failure of one or several financial institutions spreads through the financial system and increases the burden on other institutions.

The objective of this thesis is to estimate the systemic risk of the U.S. banking industry over the sample period and investigate whether financial regulations and events, including Basel I and the U.S. sub-prime mortgage financial crisis, had a significant impact on the stability of the U.S. banking system. The sources of systemic risk are also investigated in this thesis. Previous research was mainly focused on measuring the risk of individual banks. In this thesis, I will use the methodology developed by Lehar (2005) to measure systemic risk at the level of a banking system. In addition, I also attempt to examine which factors are the main drivers of systemic risk in the U.S. banking industry.

My thesis contributes to the study of systemic risk in the following ways. First, I focus on the systemic risk of the banking industry which has never been explored by using the approach developed by Lehar (2005) in previous research. In the banking industry, the term "systemic risk" is vitally concerned and is usually connected with the analysis of crises in the banking sector by both academic researchers and regulators. According to Berger, Kashyap and Scalise (1995), the U.S. banking industry has experienced a dramatic change over the last half century. They point out that due to the diversification of financial resources, the industry has been gradually losing market power over its large borrowers who can choose among many other alternatives financial sources. Also, as the financial industry has developed, the position of the banking sector has evolved from a protected monopoly, in which banks can purchase deposit funds at below-market interest rates, to a regular market sector in which they must compete with other kinds of financial institutions to raise funds. These changes indicate that the banking industry has become an integral component of the U.S. economy. Summer (2003) points out that according to historical experiences of financial crises, the huge spillover costs to the real economy often come from systemic banking crises. Thus, the stability of the economy is highly related to the safety of the U.S. banking industry.

Second, the sample period covers the implement of Basel I after 1988 and the U.S. sub-prime mortgage financial crisis in 2007 which are captured by two dummy variables. The historical experience related to financial crises simulates regulators to design financial regulations to constraint each institution's risk and improve financial safety. For instance, Basel I regulates a new risk-based capital standard which required banks to maintain 8% capital backing for loans and 0-1.6% capital backing for government securities. This new capital standard caused a shift of the U.S. bank investments from commercial lending to government securities. Wagster (1999) and Furfine (2000) report that this banks' assets re-allocation obliged by the new capital standard of Basel I restricted credit and this new standard is one important reason causing the credit crunch in 1989 which had negative effect on the health of the U.S. banking system.

The more recent financial event, the sub-prime mortgage financial crisis happened in 2007, is another important issue of concern in the U.S. banking industry. Schwarcz (2008) explains why the default in the sub-prime mortgage-backed securities markets has quickly infected the other asset-backed markets and even the entire banking system. First, different asset-backed securities are tightly connected. The default in the sub-prime mortgage damaged the confidence of investors who further avoided all other securitization products provided by banks. The second reason can be explained by adverse selection. Investors became uncertain about securitization products and the counterparties. They cannot judge whether the product or counterparty is good or not; thus, they stopped investing in all securitization products. The negative reactions of the investors had unpleasant effects on the U.S. banking industry. With the measure of systemic risk, I explore whether these two events have significantly affected the stabilization of the U.S. banking system.

Third, I investigate which factors have significantly explained systemic risk. By following Lehar (2005), I establish three systemic factors including the median correlation of assets, asset volatility and bank capitalization, and three bank specific factors consisting of time trend, bank size and the ratio of book value of equity to total assets. The systemic factors demonstrate the stability of the entire banking system and the bank specific factors reflect the financial health for each individual bank. Thus, these factors can explain the dynamic of systemic risk in the banking industry. For regulators, these explanatory variables can provide valuable information to detect the sources of systemic risk and establish regulations to maintain the stability of the system. In order to conduct the research, I use the definition of Lehar (2005) who considers a systemic crisis as an event which causes a simultaneous default of a significant number of financial institutions. Although it is not possible to identify a point at which an individual default turns out to be a systemic event, it is possible to establish two systemic risk indices. The first index, the systemic risk index based on assets (SIV), is the default probability of a certain fraction of the total assets for the entire sample of banks. This index is driven by large banks, and increase in the value of their assets or asset volatility will significantly affect this measure of risk. The second index, the systemic risk index based on the number of banks (SIN), is the probability that more than a certain fraction of banks will fail simultaneously.

Before measuring systemic risk, it is necessary to estimate the banks' market value of assets. This is done by applying a contingent claims analysis. According to Gray, Merton and Bodie (2008), a contingent claim is any financial asset whose future payoff depends on the value of another asset, which means that the contingent claim can be considered as an option. Since 1973, option pricing methodology has been used to value a wide variety of contingent claims. Based on Merton (1974), a bank's equity can be interpreted as a call option on its assets. Since the value of and volatility of a company's equity are measurable since equity is traded in the stock market, while the value of and the volatility of a company's assets are not measurable since the assets are not traded, this framework allows an estimation of the value of the banks' assets and the volatility of their assets.

Next, I build regression models to estimate the effects of Basel I and the financial crisis and investigate the relation between the systemic/bank specific variables and the systemic risk indices. To implement the regression analyses, I construct the following hypotheses:

Hypothesis 1: The implementation of Basel I has a negative effect on the health of the U.S. banking industry.

Hypothesis 2: The U.S. sub-prime mortgage financial crisis has a negative effect on the stability of the U. S. banking industry.

Hypothesis 3: The systemic factors perform better than the bank specific factors in explaining the measures of systemic risk.

The remainder of the thesis is organized as follows. Section 2 provides a brief review of the literature on systemic risk measurement. In Section 3 the database and sample selection are described. The model and methodology are introduced in Section 4. The results are reported in Section 5. Finally, conclusions are provided in Section 6.

Chapter 2. Literature Review

Research on systemic risk measurements can be generally separated into two streams. The first stream of research focuses on the definition of systemic risk. The second stream of research focuses on quantifying systemic risk.

2.1. Definition of systemic risk

Research which focuses on the definition of systemic risk may be further sub-divided into three groups, namely, bank contagion, banking panics and spillover effects.

2.1.1. Bank contagion

Bank contagion is defined by Gleeson, Hurd, Melnik, and Hackett (2011) as the spread of failures through a financial system, within which any successive default will increase pressure on the remaining components of the system. Bank contagion is mainly based on the correlation between bank defaults, bank returns, and fund withdrawals, as well as exposures among operating banks where a default of one or a small number banks would increase pressure on the remaining banks.

Jorion (2005) argues that the implementation of unitized portfolio management tools such as option pricing, portfolio insurance, and Value at Risk (VAR) would cause similar trading patterns or “herding” behavior, for instance, that investors within a group tend to buy or sell when other similar participants buy or sell. The generalized use of risk management systems has the potential to increase volatility in times of stress and reduce the safety of financial markets, which could raise systemic risk. On this basis, Jorion analyzes the risk of trading revenues of U.S. commercial banks which all apply the VAR–system for risk management and tests the relationship between the VAR-induced herding effect and the stability of financial markets after 1998. The results exhibit no increase in volatility of trading revenues during the testing period.

Bartram, Brown, and Hund (BSS) (2007) develop three approaches to measure systemic risk. The first method that they apply relies on testing the effect of financial shocks on the stock price of the sample banks that are not directly exposed to the shocks. Based on market efficiency, the negative information from financial shocks should only affect the banks which are exposed to the financial shocks. Then the abnormal performance of unexposed banks can be considered as the effect of influence from the exposed bank but not the direct effect of shocks. Thus, the abnormal stock price reaction can be interpreted as a measure of systemic risk. Using Merton's (1974) model, BSS also create maximum likelihood estimates of bank failure probabilities as a function of sample banks' characteristics which include the market value of assets, face value of debt and deposits, and asset volatility. Next, they interpret the difference between the probabilities prior to and following the financial shocks of the banks which are not directly exposed to the shocks as the measure of systemic risk. The third estimator of systemic risks that they use is implied by equity option prices for assessing systemic risk.

2.1.2. Banking panics, aggregate fluctuations, and lending booms

The second group of empirical studies related to systemic risk includes banking panics, aggregate fluctuations, and lending booms. Gorton (1988) states that bank panics may be caused by relative consumer behavior preceding the panics. The results support this hypothesis that bank panics can be explained by consumer behavior during non-panic times.

In more recent research, Bhansali, Gingrich and Longstaff (2008) extracted the credit risk component of systemic risk from credit index derivatives. They developed a linearized version of the collateralized debt obligation pricing model with the prices of credit index derivatives to extract market expectations about the nature and magnitude of credit risk in financial markets. Their results suggest that systemic risk during the 2007-2009 financial crisis is twice as large as the risk associated with the GM credit-downgrade event in May 2005. De Nicolo and Lucchetta (2009) study systemic risk from the viewpoint of macroeconomics. They investigate the impact and transmission of structurally identifiable shocks between the macro economy, financial markets, and intermediaries.

2.1.3. Spillover effects and joint crashes

The historical systemic risk literature included in the third group involves spillover effects and joint crashes in financial markets. This research is mainly based on ARCH models, extreme dependence of securities market returns, and securities market co-movements, which are not explained by fundamentals. These studies focus on currency and financial crises experienced in the second half of the 1980s and 1990s. For example, Kaminsky and Reinhart (1998) apply a simple vector auto-regression model to analyze Granger-causality between the interest rates and exchange rates of five specific Asian currencies in the pre- and post-crisis periods. The results suggest that many Granger-causal relations are detected following the Asian crisis, but none existed prior to the crisis.

2.2. Quantification of systemic risk

Research which focuses on the quantification of systemic risk may be further sub-divided into two groups, namely, the structural approach and the reduced form approach, as classified by Acharya, Pedersen, Philippon and Richardson (2011).

2.2.1. Structural approach

The papers in this group adopt a structural approach by using contingent claims analysis of the financial institution's assets. With the use of contingent claims analysis, Gray, Merton and Bodie (2008) test the sensitivity of the enterprise's assets and liabilities, originating from the risk-adjusted balance sheet, to external financial shocks. They indicate that at the national level, the sectors of an economy can be viewed as interconnected portfolios of assets, liabilities, and guarantees. Gray and Jobst (2009) develop a systemic contingent claim analysis (CCA) framework based on Black (1973) and Merton (1977) for measuring and managing financial risk and financial stability.

2.2.2. Reduced – form approach

The second group involves the papers which take a reduced-form approach, focusing on the statistical tail behavior of the financial institutions' asset returns. Hartmann, Straetmans and De Vries (2005) develop a new method based on multivariate extreme value theory to measure individual banks' exposures to each other and to systemic risk. Based on extreme stock price movements, they establish the systemic risk indicator of the banking system by constructing conditional probabilities, conditioning single or multiple bank stock price "crashes" on other banks' stock price crashes or on crashes of the market portfolio. Then the extreme co-movements measured by multivariate conditional probabilities between individual banks' stock returns are considered to be able to capture the risk of contagion from one bank to another, while the extreme co-movements between individual banks' stock returns and the market index are meant to assess the instability of the banking system during periods of financial shocks. The authors also compare the stability of the banking system in the world's two largest economies, the United States (US) and the European Union. The final results conclude that the systemic risk in the US is higher than the risk in the European Union.

Adrian and Brunnermeier (2008) introduce a new systemic risk indicator called "CoVaR" which is developed from the concept of Value at Risk (VAR), the prefix "Co" standing for conditional, contagion, or co-movement. Institution i's CoVaR relative to the system is defined as the VaR of the whole financial sector conditional on institution i being in distress. Next, the difference between the CoVaR conditional on the distress of an institution and the CoVaR conditional on the normal state of the institution provides the marginal contribution of this institution to the overall systemic risk. They also estimate the extent to which certain characteristics such as size, leverage and maturity mismatch contribute to systemic risk.

Huan, Zhou, and Zhu (2009) build an indicator of systemic risk through forward-looking price information from two highly-liquid markets, the credit default swaps market and the stock market. The information used includes credit default swap (CDS) spreads and equity prices of individual banks, from which two vital parameters of systemic risk, the probability of default of individual banks and the asset return correlations, are derived.

The work of Acharya, Pedersen, Philippon, and Richardson (2011) fills the gap between the two approaches, the structural model and the reduced-form approach. By applying an economic model involving welfare, externalities, and taxation, they demonstrate the way of using observable market data in stress tests.

Chapter 3. Data and Sample

In this thesis, I focus on the systemic risk of the U.S. banking industry. The target sample consists of 100 U.S. commercial banks ranked by size, namely, the logarithm of the book value of assets. The details of all the banks included in the target sample are shown in Table 3.1 the banks are regulated by the Federal Reserve System, Federal Deposit Insurance Corporation (FDIC), and the Comptroller of the Currency. All of these commercial banks come from the list of the large commercial banks located in the Federal Reserve Statistical Release. Through the bank IDs recorded in the list, the banks' data can be located in the Database. Some banks are excluded from the sample list due to missing information; thus, the rank of the banks in the sample is from No. 1 to No. 158.

The commercial banks in the database come from the Federal Reserve Bank of Chicago (FRB Chicago). Their data are contained in the Report of Condition and Income, also named "Call

Report". These reports provide balance sheet, income statements, risk-based capital measures and off-balance sheet data.

Data on the quarterly book value of assets, debt and equity for each bank are obtained from the Bank Regulatory Database for the period 1976 – 2010. Thus, the time range used in this research is from March 1976 to December 2010. The database also provides accounting data for commercial banks, bank holding companies, savings banks, and savings and loans institutions in the United States.

Table 3.1

Top 100 Large U.S. Commercial Banks from Federal Reserve Statistical Release

Insured U.S. - Chartered commercial banks that have consolidated assets of $300 million or more, ranked by consolidated assets as of December 31, 2012

Bank Name	National Rank	Bank ID	Bank Location	Consol Assets (Mil $)	Domestic Assets (Mil $)	Bank Name	National Rank	Bank ID	Bank Location	Consol Assets (Mil $)	Domestic Assets (Mil $)
JPMORGAN CHASE BK NA	1	852218	COLUMBUS, OH	1,896,773	1,298,562	CATHAY BK	81	595869	LOS ANGELES, CA	10,683	10,380
BANK OF AMER NA	2	480228	CHARLOTTE, NC	1,474,077	1,391,377	ISRAEL DISCOUNT BK OF NY	84	320119	NEW YORK, NY	9,980	8,515
CITIBANK NA	3	476810	SIOUX FALLS, SD	1,313,401	688,156	INTERNATIONAL BK OF CMRC	85	1001152	LAREDO, TX	9,836	9,836
WELLS FARGO BK NA	4	451965	SIOUX FALLS, SD	1,266,125	1,234,918	TRUSTMARK NB	86	342634	JACKSON, MS	9,717	9,717
U S BK NA	5	504713	CINCINNATI, OH	345,089	343,465	MB FNCL BK NA	87	656733	CHICAGO, IL	9,550	9,550
PNC BK NA	6	817824	WILMINGTON, DE	295,026	292,216	OLD NB	89	208244	EVANSVILLE, IN	9,395	9,395
BANK OF NY MELLON	7	541101	NEW YORK, NY	282,443	176,790	CITIZENS BK	90	222147	FLINT, MI	9,311	9,311
CAPITAL ONE NA	8	112837	MC LEAN, VA	250,961	250,880	FULTON BK NA	92	474919	LANCASTER, PA	9,229	9,229

STATE STREET B&TC	9	35301	BOSTON, MA	218,655	158,322	GREAT WESTERN BK	93	131650	SIOUX FALLS, SD	9,078	9,078
HSBC BK USA NA	11	413208	MCLEAN, VA	186,790	171,556	NATIONAL PENN BK	95	802110	BOYERTO WN, PA	8,348	8,348
BRANCH BKG&TC	12	852320	WINSTON SALEM, NC	178,034	177,789	FIRST CITIZENS B&T CO	96	93721	COLUMBI A, SC	8,188	8,188
SUNTRUST BK	13	675332	ATLANTA , GA	169,077	169,077	FIRST MIDWEST BK	97	1007846	ITASCA, IL	7,984	7,984
REGIONS BK	16	233031	BIRMING HAM, AL	120,421	120,188	FIRST INTRST BK	99	659855	BILLINGS, MT	7,694	7,694
FIFTH THIRD BK	17	723112	CINCINNA TI, OH	119,445	119,182	COMMUNIT Y BK NA	101	202907	CANTON, NY	7,471	7,471
NORTHERN TC	20	210434	CHICAGO, IL	97,139	70,632	UNITED CMNTY BK	105	1017939	BLAIRSVI LLE, GA	6,795	6,795
UNION BK NA	21	212465	SAN FRANCISC O, CA	96,323	95,484	PLAINSCAP ITAL BK	106	637451	DALLAS, TX	6,681	6,681
BMO HARRIS BK NA	22	75633	CHICAGO, IL	95,265	95,170	HANCOCK BK	107	463735	GULFPOR T, MS	6,618	6,618
KEYBANK NA	24	280110	CLEVELA ND, OH	87,043	86,109	PARK NB	108	489623	NEWARK, OH	6,500	6,500
MANUFACTUR ERS & TRADERS TC	26	501105	BUFFALO, NY	82,086	82,086	FIRST FNCL BK NA	109	165628	HAMILTO N, OH	6,488	6,488

DISCOVER BK	29	30810	GREENWOOD, DE	71,837	71,837	FIRST BK	110	169653	CREVE COEUR, MO	6,474	6,474
COMPASS BK	30	697633	BIRMINGHAM, AL	69,077	69,077	CITIZENS BUS BK	111	933966	ONTARIO, CA	6,357	6,357
COMERICA BK	31	60143	DALLAS, TX	65,252	64,168	WESBANCO BK	114	645625	WHEELING, WV	6,066	6,066
BANK OF THE WEST	32	804963	SAN FRANCISCO, CA	63,343	63,343	NBT BK NA	116	702117	NORWICH, NY	5,986	5,986
DEUTSCHE BK TC AMERICAS	33	214807	NEW YORK, NY	56,397	52,155	FIRST COMMONWEALTH BK	117	42420	INDIANA, PA	5,945	5,945
HUNTINGTON NB	34	12311	COLUMBUS, OH	55,955	55,955	CHEMICAL BK	118	542649	MIDLAND, MI	5,904	5,904
CITY NB	38	63069	BEVERLY HILLS, CA	28,255	28,255	ROCKLAND TC	120	613008	ROCKLAND, MA	5,760	5,760
BOKF NA	39	339858	TULSA, OK	27,934	27,934	BANK LEUMI USA	125	101019	NEW YORK, NY	5,367	5,367
SYNOVUS BK	40	395238	COLUMBUS, GA	26,425	26,425	SCBT	128	540926	COLUMBIA, SC	5,130	5,130
FIRST TN BK NA	41	485559	MEMPHIS, TN	25,285	25,283	FARMERS & MRCH BK	130	871769	LONG BEACH, CA	4,989	4,989
ASSOCIATED BK NA	42	917742	GREEN BAY, WI	23,261	23,261	UNITED BK	131	1010930	PARKERSBURG, WV	4,933	4,933
FROST BK	43	682563	SAN ANTONIO, TX	23,188	23,188	WESTAMERICA BK	132	697763	SAN RAFAEL, CA	4,914	4,914
COMMERCE BK	45	601050	KANSAS CITY, MO	22,017	22,017	CITY NB OF FL	134	814430	MIAMI, FL	4,806	4,806

FIRST-CITIZENS B&TC	47	491224	RALEIGH, NC	20,908	20,908	1ST SOURCE BK	136	991340	SOUTH BEND, IN	4,540	4,540
SUSQUEHANNA BK	52	682611	LITITZ, PA	17,968	17,968	FIRST FNCL BK NA	137	470050	ABILENE, TX	4,472	4,472
ZIONS FIRST NB	53	276579	SALT LAKE CITY, UT	17,930	17,930	WASHINGTON TR BK	138	58971	SPOKANE, WA	4,465	4,465
BNY MELLON NA	55	934329	PITTSBURGH, PA	16,894	16,894	S&T BK	141	936426	INDIANA, PA	4,381	4,381
WELLS FARGO BK NW NA	56	688079	OGDEN, UT	16,815	16,815	CENTRAL PACIFIC BK	142	701062	HONOLULU, HI	4,373	4,373
FIRST HAWAIIAN BK	57	980661	HONOLULU, HI	16,637	16,041	INTRUST BK NA	143	557858	WICHITA, KS	4,320	4,320
VALLEY NB	59	229801	PASSAIC, NJ	15,998	15,998	FIRST SECURITY BK	144	673440	SEARCY, AR	4,307	4,307
FIRSTMERIT BK NA	62	67311	AKRON, OH	14,901	14,901	FIRST MRCH BK NA	145	17147	MUNCIE, IN	4,285	4,285
UMB BK NA	63	936855	KANSAS CITY, MO	14,690	14,690	CENTENNIAL BK	146	456045	CONWAY, AR	4,234	4,234
PROSPERITY BK	64	664756	EL CAMPO, TX	14,590	14,590	RENASANT BK	147	749242	TUPELO, MS	4,169	4,169
FIRST NB OF OMAHA	65	527954	OMAHA, NE	14,500	14,500	MIZUHO CORP BK USA	148	229913	NEW YORK, NY	4,154	4,142

BANK OF HAWAII	67	795968	HONOLULU, HI	13,768	13,303	UNION FIRST MKT BK	149	693224	RICHMOND, VA	4,085	4,085
BANCORPSOUTH BK	68	606046	TUPELO, MS	13,390	13,390	NEVADA ST BK	150	456960	LAS VEGAS, NV	4,063	4,063
ARVEST BK	71	311845	FAYETTEVILLE, AR	13,200	13,200	SANDY SPRING BK	153	506922	OLNEY, MD	3,952	3,952
FIRSTBANK	74	288853	LAKEWOOD, CO	12,845	12,845	BANK OF THE OZARKS	154	107244	LITTLE ROCK, AR	3,893	3,893
FIRST NB OF PA	76	379920	GREENVILLE, PA	11,842	11,842	JOHNSON BK	155	58243	RACINE, WI	3,766	3,766
UMPQUA BK	77	143662	ROSEBURG, OR	11,794	11,794	PINNACLE BK	156	913856	LINCOLN, NE	3,758	3,758
LIFORNIA B&TC	80	837260	SAN DIEGO, CA	11,069	11,069	AMALGAMATED BK	158	661308	NEW YORK, NY	3,730	3,730

Chapter 4. Methodology

The measure of systemic risk applied is developed by Lehar (2005) and this method is able to estimate the systemic risk at the level of a banking system. This approach is based on the definition which considers a systemic crisis as an event which causes a simultaneous default of a significant number of financial institutions. It is difficult to identify a threshold at which an individual default turns out to be a systemic event; however, I am able to establish two systemic risk indices. The first index, the systemic risk index based on assets (SIV), is the default probability of a certain fraction of the total assets for the entire sample. This index is driven by large banks whose increase in their value of assets or asset risk will significantly affect this measure of risk. The second index, the systemic risk index based on the number of banks (SIN), is the probability that more than a certain fraction of banks will fail simultaneously.

In order to create these two systemic indices, it is necessary to estimate the banks' market value of assets. This estimation is done by applying a contingent claims analysis, in which a structural model is used to estimate the market value of the bank's financial assets. Giammarino et al., (1989) point out that there is usually no observable market value for a bank's assets, and it is difficult to obtain the market value for use in the regulatory process, because these assets usually consist of loans that are not actively traded in the financial markets. By following the approach of Black and Scholes (1973) who indicate that almost any asset can be viewed in an option pricing framework, Giammarino et al., (1989) treat a bank's equity as a call option on the bank's assets.

A call option allows the holder to purchase a specified stock at the exercise price during a certain period. At maturity, the value of the call option is

$$C = max(0, S - X) \tag{1}$$

where C is the value of the call option, S is the market price of the stock, and X refers to the exercise price of the option.

According to the approach developed by Black and Scholes (1973), the bank's equity, which can be interpreted as a derived asset whose value depends upon the value of the bank's assets and which often has an observable market value, has a value given by:

$$E = max(0, V - B) \qquad (2)$$

where V refers to the total value of a bank's assets and B refers to the face value of total debt liabilities. Both of the equations (1) and (2) present the mechanism linkage between the pay-off structure of equity and the pay-off structure of a call option.

4.1. Market Value of Assets

4.1.1. The Merton Framework

The framework developed by Merton (1973) is used to establish the relationship between the market value of equity and the market value of the firm. Assuming that the market value of a bank's assets V follows a geometric Brownian motion with drift μ and volatility σ:

$$dV = \mu \mathrm{V dt} + \sigma \mathrm{V dz} \qquad (3)$$

Next, equity E_t can be viewed as a call option on the assets of the bank and based on the Black-Scholes-Merton model:

$$E_t = V_t N(d_t) - B_t N(d_t - \sigma\sqrt{T}) \qquad (4)$$

$$d_t = \frac{\left[\ln\left(\frac{V_t}{B_t}\right) + \left(\frac{\sigma^2}{2}\right)T\right]}{\sigma\sqrt{T}} \qquad (5)$$

where

V_t: The market value of the bank's assets at time t;

B_t: The current notional value of the bank's debt;

N: The cumulative standard normal distribution function;

T: The time to the next audit of the bank or the maturity of the bank's debt;

σ: The volatility of the bank's assets.

In equation (4), T refers to the maturity of the bank's debt; however, it is not possible in practice that all the liabilities of the bank have the same maturity. Merton (1977) points out that the length of time until maturity can be reinterpreted as the length of time until the next audit of the bank's assets. Then, in the next audit period, if the value of the bank's assets is less than the value of the liabilities, the auditors will declare bankruptcy of the bank.

Ronn and Verma (1986), using Ito's lemma, derive a linear relationship between the volatility of equity σ_E and the volatility of asset σ. This is given by:

$$\sigma_E = \left(\frac{V}{E}\right)\left(\frac{\partial E}{\partial V}\right)\sigma \tag{6}$$

The value of σ_E can be estimated using the GARCH model. The equations (4) and (6) are two equations with two unknowns, which can be solved by the Newton-Raphson method to obtain the total market value of the assets of the bank, V, and the standard deviation of V, σ.

Under the linear volatility relationship used in Ronn and Verma (1986) to obtain the equity volatility, σ_E is inappropriately considered to be a constant. In order to overcome this problem, Duan (1994) and Duan (2000) develop a new method to obtain maximum likelihood estimates based on a time series of the value of the bank equity.

4.1.2. Maximum Likelihood

The main purpose of the maximum likelihood estimation is the transformation from observed data to unobserved data. In this method, the most important part is the derivation of a likelihood function based on the observed data. Duan (1994) and Duan (2000) apply standard theory on differentiable transformations to conclude that the maximum likelihood function is given by:

$$L(E,\mu,\sigma) = -\frac{m-1}{2}\ln(2\pi) - \frac{m-1}{2}\ln\sigma^2 - \sum_{t=2}^{m}\ln\widehat{V}_t(\sigma) - \sum_{t=2}^{m}\ln(N(\widehat{d}_t))$$

$$-\frac{1}{2\sigma^2}\sum_{t=2}^{m}\left[\ln(\frac{\widehat{V}_t(\sigma)}{\widehat{V_{t-1}}(\sigma)} - \mu\right] \tag{7}$$

where $\widehat{V}_t(\sigma)$ is the solution to equation (4) corresponding to a sequence E = (E_t), $t \in \{1, \ldots m\}$, of equity value and a sequence B = (B_t), $t \in \{1, \ldots m\}$, of the notional value of the bank's debt. The $\widehat{d}_t$ corresponds to the d_t in equation (5). Based on Lehar (2005), the equity E_t is treated as a call option on the assets V_t with a strike price equal to the face value of the bank's debt at the maturity T that is assumed to equal to one year.

The sample period is from March 1976 to December 2010. The first 40 quarters, from March 1976 to December 1985, are used as an estimation period to calculate the results for the 41st quarter. Then the estimation window is rolled forward by one quarter to obtain the results for the next quarter. Thus, the relevant estimates are obtained for each quarter of the test period from March 1986 to December 2010.

There are two unknowns, V_t and its volatility σ in equation (4). A numerical method is applied to obtain the $\widehat{V}_t(\sigma)$. First, a series of 100 values for σ are assumed ranging from 0.01 to 1 at intervals of 0.01. Next, coupled with a sequence of equity values E_t and face value of debt B_t, each σ is introduced in equation (4) to obtain a series of values of $\widehat{V}_t(\sigma)$ which correspond to E_t and B_t. Thus, a matrix of $\widehat{V}_t(\sigma)$ with 100 rows and 140 columns is constructed. In the next step, each row of $\widehat{V}_t(\sigma)$ with the corresponding σ is substituted into equation (7). Through maximizing the likelihood function, an optimum set of $\widehat{V}_t(\sigma)$ with corresponding σ is obtained. The estimation window is 40 quarters and corresponds to the previous 10 years. The previous 40 quarters are used to estimate the next quarter's values; thus, the value of m in equation (7) is 41. The estimation window is then rolled forward by one quarter. This procedure provides parameter sets of μ and σ and the optimum market value of asset $\widehat{V}_t$ for each quarter in the estimation window for all banks over the entire sample period from the first quarter of 1986 to the last quarter of 2010. Table 4.1 below shows summary information of the market value of assets for the sample banks.

Table 4.1 Summary statistics on the market value of assets of all banks included in the sample

Type	Total assets (market value in thousand. USD)			
	1986	2010	Maximum (2010)	Minimum (2010)
All banks	1,817,285	29,542,889	5,438,038	4,344
Top 10 banks	1,099,510	22,822,577	5,438,038	438,928
Last 10 banks	20,663	135,172	18,488	10,193

4.1.3. Robustness consideration

For the robustness consideration, the set of σ can be increased from one hundred to one thousand ranging from 0.001 to 1, which can improve the accuracy of estimation of the parameters μ and σ. This robustness check is applied to certain banks in the sample and the results for Associated Bank are displayed in Table 4.2 below. We note that the values of μ under σ = (0.01:0.01:1) are very close to the values of μ under σ = (0.001:0.001:1). Thus, compared with the enormous increase in computation time, the accuracy of the parameters does not significantly improve. Thus the set of one hundred σ's is applied in this method.

Table 4.2 Comparison between the parameters under the two sets of σ for Associated Bank

□ σ= (0.01:0.01:1) indicates the set of 100 σ from 0.01 to 1, under which the values of μ are the same as the values of μ under σ= (0.001:0.001:1).

Date	**□ σ=(0.01:0.01:1)**		**□ σ=(0.001:0.001:1)**	
	μ□	**σ□**	**□ μ**	**σ□**
31/03/1986	0.021	0.21	0.021	0.214
30/06/1986	0.0203	0.21	0.0203	0.214
30/09/1986	0.0207	0.21	0.0207	0.214
31/12/1986	0.0212	0.22	0.0212	0.215
31/03/1987	0.017	0.22	0.017	0.222
30/06/1987	0.0178	0.22	0.0178	0.221
30/09/1987	0.0176	0.22	0.0176	0.221
31/12/1987	0.018	0.22	0.018	0.221
31/03/1988	0.0166	0.22	0.0166	0.224
30/06/1988	0.0165	0.22	0.0165	0.224
30/09/1988	0.0178	0.23	0.0178	0.229
31/12/1988	0.0166	0.23	0.0166	0.229
31/03/1989	0.0207	0.24	0.0207	0.242
30/06/1989	0.0194	0.24	0.0195	0.244
30/09/1989	0.0198	0.24	0.0198	0.244
31/12/1989	0.0205	0.24	0.0205	0.243
31/03/1990	0.0191	0.24	0.0191	0.243
30/06/1990	0.0185	0.24	0.0185	0.243
30/09/1990	0.018	0.24	0.018	0.242
31/12/1990	0.0193	0.24	0.0193	0.24

4.2 Dynamics of the Market Value of Assets

4.2.1. Variance and Covariance of market value of assets

Through the method displayed in the section 4.1, I am able to build a time series of the market values of individual banks' assets. The methodology of obtaining the two vital input variables for estimating systemic risk, asset correlation and asset volatilities, is described in this section. These two input variables are generated from variances and covariances of the market values of the banks' assets which can be estimated by applying the exponentially weighted moving average model (EWMA). This model was originated by RiskMetrics, which is the standard in market risk management developed by JP Morgan.

Table 4.3 below presents the formulas used to compute the equally and exponentially weighted volatility for a given set of T returns. The r_t in the following equations represents the return on assets at time t and $\bar{r}$ is the average of the set of T returns. The parameter λ ($0< \lambda<1$) is a decay factor.

Table 4.3 Volatility estimators

Equally weighted	**Exponentially weighted**
$\sigma = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t - \bar{r})^2}$	$\sigma = \sqrt{(1-\lambda)\sum_{t=1}^{T}\lambda^{t-1}(r_t - \bar{r})^2}$

The equally weighted volatility is used by the simple moving average (SMA). The exponentially weighted volatility is used by the exponentially weighted moving average model (EWMA). Compared with SMA which equally treats previous volatilities, one important advantage of EWMA is that it can capture the dynamic features of volatility. According to the RiskMetrics framework, in volatility estimation, the later observations usually carry the higher weight than the previous ones because the most recent shock is reflected more in the market rather than that due to the observations in the distant past. Thus, the aim of using the EWMA model is to apply more weights to the more recent volatilities. This is different from the SMA that can only equally assign the weight to each observation.

For each quarter in the sample period a covariance matrix $\sum_t$ of asset returns is estimated by applying the EWMA model. The EWMA model relies on the decay factor λ (0< λ<1). This parameter affects the relative weights given to older and more recent observations of returns in estimating volatility. The more recent observations are applied more weights than the older observations.

The decay factor λ is set to 0.94 following RiskMetrics. The covariance σ_{ij} between the asset value of bank i and the asset value of bank j at time t is measured by the following equation:

$$\sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1+\lambda)\ln\left(\frac{V_t^i}{V_{t-1}^i}\right)\ln\left(\frac{V_t^j}{V_{t-1}^j}\right) \tag{8}$$

The variance-covariance matrix is estimated by applying equation (8) to each asset and pair of assets in the portfolio. Thus, the EWMA model is straightforward and convenient to deal with when using a large number of assets. In addition, the variance-covariance matrix is guaranteed to be positive semi-definite, which is a very important prerequisite of the subsequent systemic risk estimation.

In the estimation procedure, the time series of asset values of each bank as obtained in the last section is first converted to an asset return. Then the variance-covariance of these bank asset values is used to form the $\lambda\sigma_{ij,t-1}$ in equation (8). Next, the variance and covariance of the banks at each time t are extracted by applying equation (8).

4.2.2 Correlation and volatility

Through the equation (8), the dynamics of the variance and covariance can be formed. From both the variance and covariance, I can also form the dynamic of the correlation of banks' assets. The standard deviation is considered as the volatility of banks' assets. Both of the median correlation and the median volatility are used to demonstrate the dynamics of the market value of assets. In order to explore the intuition behind the dynamics, I follow Lehar (2005) to establish certain regression models to explain the median correlation of a bank to all other banks and the median volatility, and the dependent and independent variables developed by Lehar are also introduced into the regression analyses.

Dependent variables

The three dependent variables are all related to the factors of the entire banking system. Based on the methodology of section 4.2.1, I generate a vector of quarterly variances for each bank and a set of quarterly covariances for every pair of banks. The quarterly variances for each bank are easily transformed into quarterly standard deviations. The median value of the quarterly standard deviation is treated as the volatility of assets. Using the quarterly variance and covariance, I also obtain quarterly correlation for each pair of banks. Both the median value of the correlation and volatility in every quarter are used to describe the dynamic of the assets of the U.S. banking system by Lehar (2005), they are also considered as systemic factors in the following regression analyses.

The other systemic factor is the median bank capitalization ratio which is equal to the assets of the bank divided by its debt. Bond and Crocker (1993) explored the relation between bank capitalization and deposit insurance. They found that premiums charged by insurance contracts depend on bank risk which is indicated by the level of capitalization. They also report that bank capitalization can reduce the probability of bankruptcy and be used as a complementary tool for deposit insurance to protect depositors from the risk of bank failure. Hughes and Mester (1998) point out that higher level of bank capitalization can give depositors a signal of safety and reduce the probability of a liquidity crisis of a banking system. Thus, bank capitalization plays a very important role in deciding the financial health of the entire banking system.

Independent variables

Three independent variables related to bank specific factors are established. The first factor is the time trend which reflects the direction in each bank's market value of assets. This factor indicates whether a bank's asset value is increasing or decreasing and at what rate. The first quarter, March 1986, is the base quarter which has a value for this factor of 100% and every subsequent quarter until December 2010 is referred to as the quarter under analysis. The value of this factor for each quarter under analysis equals the asset value for the quarter under analysis divided by the asset value in the base quarter. This factor can be considered as an indicator of a bank's financial situation based on asset value.

The second factor is bank size (SIZE), which is measured as the logarithm of the market value of assets in each quarter. Since larger banks are able to engage in more different markets, they have the potential to be more diversified. The last factor is the ratio of book value of equity to total assets (EQBK). EQBK reflects the financial health and long-term profitability of the banks. This ratio is used to determine the banks' overall financial situation. A high ratio indicates that the bank is mainly owned by its shareholders, while a low ratio means that the bank is burdened by a high level of debt, which will make it difficult to raise funds due to concerns about its solvency. A bank with a higher value for EQBK has a higher capital cushion to engage in riskier financial markets and become more diversified. This factor is based on the assumption that the banks with a higher level of capital cushion have the ability to invest in a riskier market.

Regression models

The subsequent regression models (9) and (10) are used to explain the dynamics of the median correlation and the median volatility of the assets. The regression model (11) is applied to investigate the median capitalization of the banking system. The three dependent variables could be indicators of the banking system's stability. If the median correlation is high, this implies that the banks in the system are tightly connected and the default probability of the entire system is high. Bond and Crocker (1993) and Hughes and Mester (1998) conclude that capitalization reduces the probability of bankruptcy; thus, a high capitalization ratio lowers the default probability of the banking system.

The three bank specific factors are time trend, size, and EQBK, all of which are treated as the independent variables. These three factors are related to each individual bank's financial health. The bank with a high time trend, a large size or a large value for EQBK may be active in various markets and be more diversified, which will reduce the probability of default.

Hypothesis 4: The three independent variables are negatively related to the median correlation and volatility, and positively related to capitalization.

$$\mathrm{Corr}_t = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \varepsilon_t \tag{9}$$

$$\mathrm{Vol}_t = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \varepsilon_t \tag{10}$$

$$\mathrm{Cap}_t = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \varepsilon_t \tag{11}$$

The Corr, Vol, and Cap in equations (9), (10), and (11) respectively represent the median correlation, the median volatility and the median bank capitalization. These symbols are also applied in all subsequent regression models and represent the same variables. All dependent and independent variables are quarterly median values for all the banks.

Over the sample period, the U.S. banking industry has gone through a historic development and may have been affected by both economic and regulatory factors. Thus, two dummy variables capturing the effects of certain events related to regulation and to the economy are used in the regression analysis. The first dummy variable concerns the effect caused by the implementation of Basel I.

As an international financial regulation, Basel I may affect the worldwide banking system. In the United States, the environment for bank capital regulation in the 1990s was a result of the overhaul of Basel I which was implemented in the beginning in 1990. Wagster (1999) reports that Basel I's risk weighting scheme obliged banks to hold 8% capital backing for loans and 0-1.6% capital backing for government securities, which simulated the U.S. banks to re-allocate the assets to meet this new capital standards. Furfine (2000) points out that since the application of the new capital standards, a shift has occurred in the U.S. commercial bank portfolios. These banks simultaneously began to reduce their investments in commercial lending and increase their holdings of government securities. Furfine also indicates that the amount of bank credit invested in commercial and industrial loans decreased from 22.5% in 1989 to around 16% in 1994. During the same period, the share of bank credit invested in U.S. government securities increased from over 15% to around 25%. This shift may reduce the volatility due to the increase of government securities; however, the level of correlation would be improved because the bank investments become more concentrated.

The dummy variable DUM89_94 that is introduced the regression models (12), (13), and (14) to capture the effect of Basel I. The value of DUM89_94 is 1 for the years from 1989 to 1994 and 0 for other years. All other variables in these three equations are the same as the variables in model (9), (10), and (11).

The three regression models are re-conducted:

Hypothesis 5: The dummy variable capturing the effect caused by Basel I improves the level of the median correlation, and reduces volatility and capitalization.

$$\mathrm{Corr}_t = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \alpha_4 \mathrm{DUM89\_94}_t + \varepsilon_t \tag{12}$$

$$\mathrm{Vol}_t = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \alpha_4 \mathrm{DUM89\_94}_t + \varepsilon_t \tag{13}$$

$$\mathrm{Cap}_t = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \alpha_4 \mathrm{DUM89\_94}_t + \varepsilon_t \quad (14)$$

The second dummy variable focuses on the economic recession and the financial crisis. The most recent influential event is the U.S. sub-prime mortgage financial crisis which started in 2007. Reinhart and Rogoff (2008) investigate the sub-prime mortgage financial crisis over the period 2007 to 2008 and compare it with earlier post-war banking crises in the United States. Thus, the second dummy variable DUM07_08 captures the sub-prime mortgage financial crisis of the years 2007 and 2008.

Hypothesis 6: The dummy variable of the financial crisis increases the level of the median correlation and volatility, and reduces capitalization.

$$\mathrm{Corr}_{i,t} = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \alpha_4 \mathrm{DUM07\_08}_t + \varepsilon_t \quad (15)$$

$$\mathrm{Vol}_t = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \alpha_4 \mathrm{DUM07\_08}_t + \varepsilon_t \quad (16)$$

$$\mathrm{Cap}_t = \alpha_0 + \alpha_1 \mathrm{Trend}_t + \alpha_2 \mathrm{Size}_t + \alpha_3 \mathrm{EQBK}_t + \alpha_4 \mathrm{DUM07\_08}_t + \varepsilon_t \quad (17)$$

The dummy variable DUM07_08 has a value of 1 for the years 2007 to 2008 and a value of 0 for other years.

4.3. Measures of systemic risk

4.3.1. Systemic risk indices

A common factor in the various definitions of systemic risk is a trigger event, such as an economic shock or an institutional failure resulting in a series of negative economic consequences which lead to a simultaneous default of a large number of financial institutions. Lehar (2005) points out that the trigger event of a systemic crisis cannot be identified. Thus, this method is not an attempt to measure the systemic risk caused by contagion that implies that the default of an individual bank can directly cause the default of other banks or even the entire banking system through linkages in the banking market. However, it is possible to measure the probability of a systemic crisis by using the portfolio approach, as for example by the probability of a certain fraction of defaults over a given time horizon.

Thus, Lehar (2005) defines a systemic crisis as an event in which a considerable number of financial institutions fail simultaneously. Next, the term "systemic risk" is defined by an index which captures the risk caused by correlated asset portfolios. Once the joint dynamic of bank asset portfolios are estimated, certain indicators of systemic risk can be identified. The first one is derived from the probability that banks with total assets of more than a certain percentage Ɛ of all banks' assets become bankrupt within a short period of time. This probability is defined as the systemic risk index based on assets SIV(Ɛ) and is represented by:

$$V_{j,t+1} < B_{j,t+1} \quad \forall j \in J \subset F, \; \sum_{j \in J} V_{j,t} > \mathcal{E} \sum_{i \in F} V_{i,t} \tag{18}$$

where J is the fraction of defaulting banks and F is the total number of sample banks. In equations (18) and (19), both $V_{j,t+1}$ and $B_{j,t+1}$ are the value of assets and the book value of debt in the next six months t+1 for each bank j. A bank will be considered to be bankrupt if the market value of its assets is lower than the notional value of its debt within the next six months. The inequality $\sum_{j \in J} V_{j,t} > \mathcal{E} \sum_{i \in F} V_{i,t}$ indicates that if the sum of the assets of defaulting banks J exceeds a certain fraction Ɛ of the sample's total assets, then the banking system is considered to have failed.

In addition, regulators are also concerned that sometimes the number of defaulting financial institutions may exceed a certain fraction of the total number of financial institutions. The probability that more than a certain fraction ϕ of banks will become insolvent at the same time is defined as the systemic risk index based on the number of banks SIN(ϕ) and is defined by:

$$V_{j,t+1} < B_{j,t+1}\ \forall j \in J \subset F, \#J > \phi\#F \tag{19}$$

where the last inequality $\#J > \phi\#F$ implies that the entire system will default if the number of failed banks exceeds a certain fraction ϕ of all the sample banks.

The value of $B_{j,t+1}$ is found in the financial statements of each bank at time t+1 and $V_{j,t+1}$ is generated by simulating correlated asset paths. Then $V_{j,t+1} < B_{j,t+1}$ will be used as the criterion of bank failure. The values of the fractions Ɛ and ϕ that will be considered are 5%, 10% and 15%. Then the default probabilities for 5%, 10% and 15% of total assets and the total number of institutions are calculated by using Monte Carlo simulation.

4.3.2. Correlated asset paths

According to Lehar (2005), in the measurement of the default probability, the market value of each bank's total assets is governed by a Geometric Brownian motion:

$$V_j(t) = \mu_j V_j d_t + V_j dX_j \tag{20}$$

where X represents an n-dimensional Brownian motion with variance-covariance matrix Σ as developed in equation (8) in section 4.2 for each time t. To consider the correlation among banks $V_j(t)$ is defined as

$$V_j(t) = V_j(0) * e^{(\mu_j t + X_j(t) - \frac{1}{2}\sigma_{jj}^2 t)} \tag{21}$$

where $X_j(t)$ follows a multivariate normal distribution with E[$X_j(t)$]=$0_{n,1}$, an n×1 vector of zeros and Var[$X_j(t)$]=tΣ, Σ is the n-dimensional variance-covariance matrix and σ_{jj}^2 is the jth diagonal element of Σ. $V_j(t)$ is simultaneously simulated for all the banks. Applying the Cholesky decomposition, Σ can be replaced by $U^T U$ in which the U^T is an n-dimensional lower triangular matrix. Lehar introduces a new variable W which can be defined as

$$W = \sqrt{t}U^{T}Y \tag{22}$$

where W follows the same distribution as $X_j(t)$. In the Monte Carlo simulation and Y is an n×1 vector of independent variables which follow a normal distribution. Then the W is used to substitute for $X_j(t)$ and $V_j(t)$ is rebuilt as

$$V_j(t) = V_j(0) * e^{(\mu_j t + W_j - \frac{1}{2}\sigma_{jj}^2 t)} \tag{23}$$

Using Cholesky decomposition, the joint process of all banks' market value of assets can be simulated. I use MatLab to generate the random vector Y and simulate the systemic risk indexes.

4.3.3. Monte Carlo simulation

The market value of assets for each sample bank is simulated by using equation (23) in section 4.3.2. The $V_j(0)$, a 100×1 vector, consists of all the 100 banks' market value of assets in the first quarter. By applying equation (23), a 100×1 vector $V_j(t)$ the market value of asset for each bank in the next six month is generated. Next, both equation (18) and equation (19) are used to estimate the two systemic indices, SIV, systemic risk based on assets, and SIN, systemic risk based on the number of banks.

The 100×1 vector of $V_j(t)$ generated from equation (23) is introduced in equation (18) and compared with the vector of $B_j(t)$. If the value of $V_j(t)$ is less than the value of $B_j(t)$, the bank j is considered default. Then the defaulting banks are used in the last inequality $\sum_{j \in J} V_{j,t} > \varepsilon \sum_{i \in F} V_{i,t}$ of equation (18). If the total amount of all the defaulting banks' market value of assets exceeds the fraction ε of the sum of the entire sample's asset value, the system is considered to have failed. This simulation is repeated n times. Then the SIV equals the frequency of defaults divided by the number of simulations.

Similarly, the SIN is estimated by applying equation (19), in which the vectors $V_j(t)$ and $B_j(t)$ are used to judge whether each individual bank defaults. The last inequality $\#J > \phi\#F$ is used to decide whether the system defaults. If the number of defaulting banks exceeds a certain fraction of the total number of banks in the sample, the system is considered to have failed. This simulation is also repeated n times. Then the index SIN equals the frequency of system defaults divided by the number of simulations.

As explained in section 4.1.2, I obtain a vector of quarterly market value of assets for each bank from March 1986 to December 2010. However, in the calculation of systemic risk indices, the comparison between $V_j(t)$ and $B_j(t)$ starts in the next six months following March 1986. Thus, the systemic risk indices are calculated for the period September 1986 to December 2010.

Based on the principle of probability theory, in order to increase the accuracy of the systemic risk indices, I have to conduct a large number of simulations. In this thesis, I follow Lehar (2005) and conduct 1 million, 2 million and 3 million simulations. I also use also three different values of the fraction 5%, 10% and 15% for both $\mathcal{E}$ and ϕ.

4.4 The systemic risk indices

The two systemic risk indices SIV and SIN are estimated by using Monte Carlo simulation. Next, the systemic and bank specific factors and the two dummy variables developed in section 4.2.2 are introduced in this regression analysis, through which I am able to address which factors contribute to systemic risk and decide whether the effects of the financial regulation and crisis have influence on the financial health of the U.S. banking industry.

Hypothesis 7: With regard to the systemic factors, the median correlation and volatility have positive relations with the indices; capitalization is negatively related to the indices.

The subsequent two regression equations (24) and (25) investigate the relation between the systemic risk indices and systemic factors and consider the effect of Basel I (DUM89_94). For comparison, the bank specific factors are included in the regression models (26) and (27). All dependent and independent variables are the median values for every bank in each quarter.

$$\mathrm{SIV_t} = \alpha_0 + \alpha_1 \mathrm{Corr_t} + \alpha_2 \mathrm{Vol_t} + \alpha_3 \mathrm{Cap_t} + \alpha_4 \mathrm{DUM89\_94_t} + \varepsilon_t \quad (24)$$

$$\mathrm{SIN_t} = \alpha_0 + \alpha_1 \mathrm{Corr_t} + \alpha_2 \mathrm{Vol_t} + \alpha_3 \mathrm{Cap_t} + \alpha_4 \mathrm{DUM89\_94_t} + \varepsilon_t \quad (25)$$

$$\mathrm{SIV_t} = \alpha_0 + \alpha_1 \mathrm{Trend_t} + \alpha_2 \mathrm{SIZE_t} + \alpha_3 \mathrm{EQBK_t} + \alpha_4 \mathrm{DUM89\_94_t} + \varepsilon_t \quad (26)$$

$$\mathrm{SIN_t} = \alpha_0 + \alpha_1 \mathrm{Trend_t} + \alpha_2 \mathrm{SIZE_t} + \alpha_3 \mathrm{EQBK_t} + \alpha_4 \mathrm{DUM89\_94_t} + \varepsilon_t \quad (27)$$

The other four regression models (28), (29), (30), and (31) are also conducted to explore whether the systemic factors and bank specific factors contribute to the risk indices concerning the effect of the U.S. sub-prime mortgage financial crisis.

$$\mathrm{SIV_t} = \alpha_0 + \alpha_1 \mathrm{Corr_t} + \alpha_2 \mathrm{Vol_t} + \alpha_3 \mathrm{Cap_t} + \alpha_4 \mathrm{DUM07\_08_t} + \varepsilon_t \quad (28)$$

$$\mathrm{SIN_t} = \alpha_0 + \alpha_1 \mathrm{Corr_t} + \alpha_2 \mathrm{Vol_t} + \alpha_3 \mathrm{Cap_t} + \alpha_4 \mathrm{DUM07\_08_t} + \varepsilon_t \quad (29)$$

$$\mathrm{SIV_t} = \alpha_0 + \alpha_1 \mathrm{Trend_t} + \alpha_2 \mathrm{SIZE_t} + \alpha_3 \mathrm{EQBK_t} + \alpha_4 \mathrm{DUM07\_08_t} + \varepsilon_t \quad (30)$$

$$\mathrm{SIN_t} = \alpha_0 + \alpha_1 \mathrm{Trend_t} + \alpha_2 \mathrm{SIZE_t} + \alpha_3 \mathrm{EQBK_t} + \alpha_4 \mathrm{DUM07\_08_t} + \varepsilon_t \quad (31)$$

Chapter 5. Results

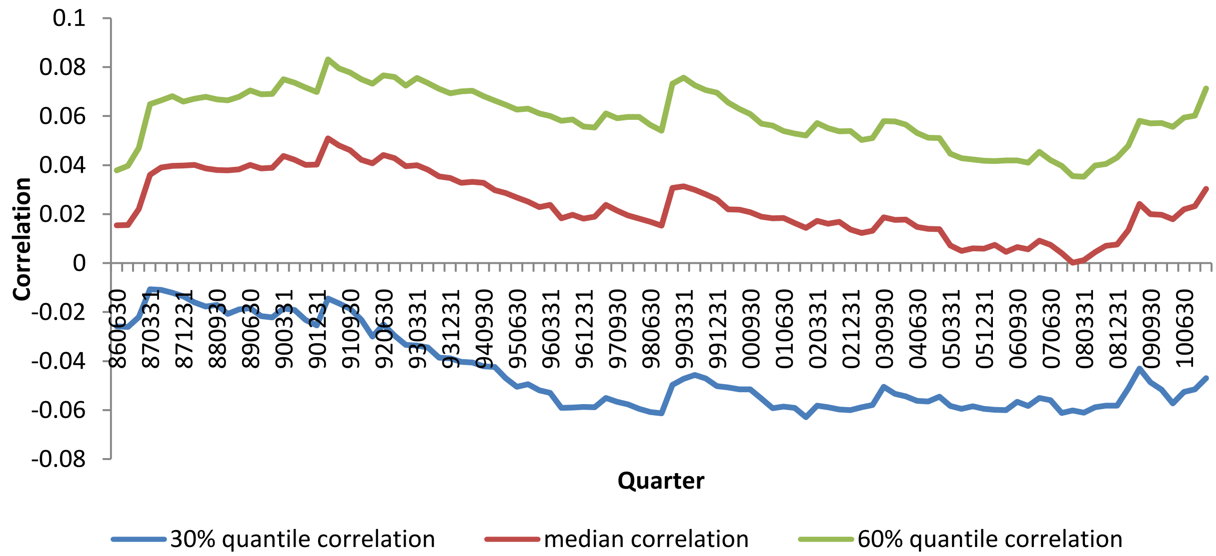
5.1 Dynamics of market value of assets

5.1.1 Median correlations and volatilities

Based on the analysis of section 4.2.1 I obtain the median correlation between bank assets that is displayed in Figure 5.1. Figure 5.2 also plots the 30% quantile and 60% quantile correlations over the sample period. In the words of Lehar (2005), compared to equity correlations, the asset correlations provide superior information as they are not influenced by changes in the capital structure.

Figure 5.1 below displays the quarterly estimates of median correlations between U. S. bank assets over the quarters June 1986 through December 2010. There are a total of 4950 pairwise correlations for the 100 banks in the whole sample, from which the median correlations are obtained.

Figure 5.1 Quarterly median correlations for the U.S. banking system



The median correlations for the sample are positive over the entire sample period and generally show a downtrend between March 1987 and March 2008. There are two peaks in the median correlations in March 1990 and March 1999. Following the first quarter of 2008, the median correlations begin to trend upwards.

Over the whole period, although there are several sharp increases captured by the model, the entire set of the median correlations of the U.S. commercial banks still remain at a low level compared with the median correlations between asset portfolios of European and Japanese banks, as estimated by Lehar (2005). From January 1988 to December 2002, the median correlations of bank assets in Europe were above 0.2 and the peaks were beyond 0.4. In the Japanese banking sector, the median correlations were even higher than in Europe and remained above 0.4. However, in the same period, the median correlations in the U.S. banking industry ranged from to the lowest 0.014 in 2002 to the highest 0.051 in 1991, which indicates that the asset portfolios of U.S. banks were less interconnected.

Figure 5.2 shows the quarterly estimates of median volatilities of U. S. bank assets over the quarters June 1986 through December 2010. For each quarter, the volatilities of each of the 100 banks' assets are estimated by applying the EWMA, from which the median volatilities are obtained.

Figure 5.2 Quarterly median volatilities for the U.S. banking system

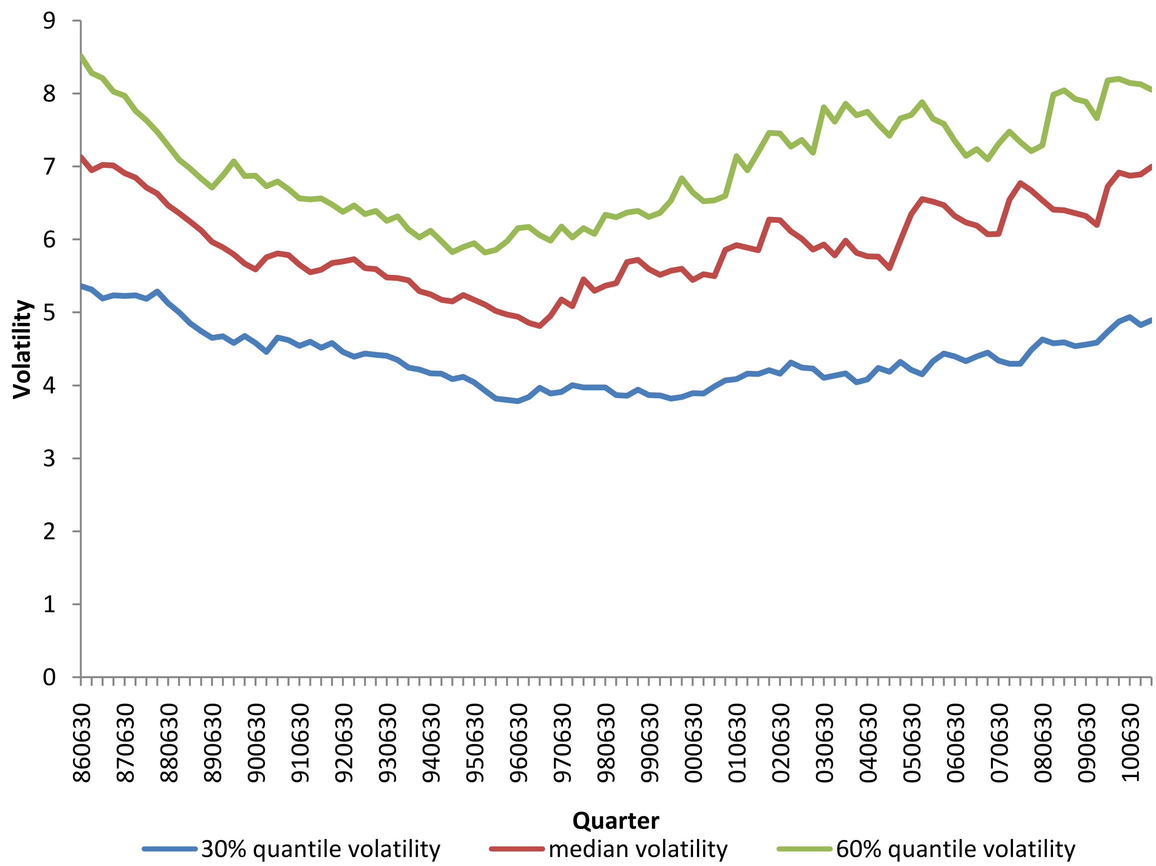


Figure 5.2 presents the trend of the median volatilities of the banks' asset portfolios. We see that the median volatilities are very stable, as are the median correlations. There is a slight decrease from 1986 to 1996, and then the median volatilities slowly return to the 1986 values in 2010. Certain bank specific factors may have some explanatory power for understanding the changes in the median volatilities of banks' assets.

5.1.2. Relationship between systemic and bank specific factors

The regression models (9) and (10) in subsection 4.2.2 are used to investigate which of the explanatory variables time trend, size, and EQBK significantly affect the two systemic factors, the median correlation and volatility, and capitalization. The regression model (11) in subsection 4.2.2 is used to investigate which of the two explanatory variables time trend and size affect the third systemic factor, the median capitalization ratio. As explained in subsection 4.2.2, EQBK is not included as an independent variable in equation (11) to avoid the problem of endogeneity. The results of these three regressions are reported in Table 5.1.

The R-squares shown in Table 5.1 are very high which indicates that all three regression models perform very well. The coefficients of time trend in all three regressions imply that this variable is significantly related to the three dependent variables. However, time trend has a positive relationship with the median correlation and volatility, which violates hypothesis 4.

Size perfectly explains the three dependent variables in all three regression analyses. It significantly reduces the level of the median correlation and volatility, and increases the median capitalization. EQBK is negatively related with the median correlation and volatility. The results for size and EQBK confirm the hypothesis 4.

Table 5.1 Relationship between the systemic factors and the bank specific factors
Results obtained from the panel regression analysis which explains the median correlation of a bank's asset portfolio with the asset portfolios of all other banks in the sample (Median Correlation), the volatility of a bank's assets (Volatility), and a bank's capitalization ratio (Capitalization). The explanatory variables are the time trend of the bank's assets (Trend), the bank's size (Size), and the ratio of the bank's book value of equity to total assets (EQBK).

	Median Correlation	Volatility	Capitalization
N	99	99	99
R-Squared	0.7252	0.5894	0.8952
Adjusted R-Squared	0.7164	0.5763	0.8930
Intercept	0.31327**	25.56928**	-6.23787*

	(7.63)	(11.38)	(-2.10)
Trend	0.00002**	0.00346**	0.00235**
	(3.93)	(10.41)	(5.52)
Size	-0.01795**	-1.45012**	0.60592*
	(-5.80)	(-8.57)	(2.79)
EQBK	-0.36407**	-1.75936	
	(-4.00)	(-0.35)	

Note:
*** and ** statistically significant at the 5% and 1% level respectively.**

EQBK is not included in the regression analysis on capitalization to avoid the problem of endogeneity.

Next, the effect of implementation of the Basel I is analyzed by conducting the regression analyses of equations (12), (13) and (14). The R-squareds shown in Table 5.2 are slightly higher than the corresponding values in the Table 5.1. Both Size and EQBK are still negatively related to median correlation and volatility, and positively related to capitalization, which is consistent with the conclusion of the previous regression analysis. The improvement in this analysis is that the correlation coefficient between volatility and EQBK becomes significant at the 5% level.

The coefficients of the dummy variable DUM89_94 in the regressions with median correlation and volatility as dependent variables are 0.00839 and -0.50406 respectively and are both statistically significant at the 1% level. The negative relation between DUM89_94 and volatility confirms hypothesis 5; due to the shift of bank investment from riskier financial markets to government securities, the volatility of the U.S. banking industry decreases in the period 1989 to 1994. Also, this shift makes the bank investment more concentrated; the positive relation between the dummy variable and the median correlation indicates that the interconnectedness between banks' investment portfolios increases after the implement of the Basel I in the United States.

Table 5.2 The effect of the implementation of Basel I on the relationship between the systemic and bank specific factors
Results obtained from the panel regression analysis which explains the median correlation of a bank's asset portfolio with the asset portfolios of all other banks in the sample (Median Correlation), the volatility of a bank's assets (Volatility), and a bank's capitalization ratio (Capitalization). The explanatory variables are the time trend in the bank's assets (Trend), bank size (Size), the ratio of the bank's book value of equity to total assets (EQBK), and a dummy variables which assumes a value of 1 for the years 1989 and 1994 and 0 otherwise to capture the effect of implementation of the Basel Accord.

	Median Correlation	**Volatility**	**Capitalization**
N	99	99	99
R-Squared	0.7720	0.6739	0.8962
Adjusted R-Sq	0.7622	0.6598	0.8929
Intercept	0.25536**	29.05037**	-7.29357*
	(6.41)	(13.61)	(-2.30)
Trend	0.00002**	0.00384**	0.00229**
	(3.06)	(12.48)	(5.32)
Size	-0.01494**	-1.63065**	0.67750*
	(-5.12)	(-10.45)	(2.96)
EQBK	-0.21914*	-10.47081*	
	(-2.44)	(-2.18)	
DUM89_94	0.00839**	-0.50406**	0.13874
	(4.37)	(-4.91)	(0.98)

Note:
*** and ** statistically significant at the 5% and 1% level respectively.**
EQBK is not included in the regression analysis on capitalization to avoid the problem of endogeneity.

Next, the effect of the U.S. sub-prime mortgage crisis on the relationship between the systemic and bank specific factors is analyzed. The results of the regression models (15) and (16) as shown in Table 5.3 indicate that both Size and EQBK have strong explanatory power for the median correlation and volatility. The negative relationships with median correlation of assets and the volatility imply that larger bank sizes and higher capitalization ratios will reduce the effect of systemic factors. However, the dummy variable is negatively related with the median correlation which is not consistent with hypothesis 6, according to which the sub-prime mortgage crisis should increase the median correlation and further increase the probability of default, which is not captured by the dummy variable.

Table 5.3 The effect of the U. S. sub-prime mortgage crisis on the relationship between the systemic and bank specific factors
Results obtained from the panel regression analysis which explains the median correlation of a bank's asset portfolio with the asset portfolios of all other banks in the sample (Median Correlation), the volatility of banks' assets (Volatility), and the banks' capitalization ratio (Capitalization). The explanatory variables are time trend of the banks' assets (Trend), bank size (Size), the ratio of book value of equity to total assets (EQBK), and dummy for the time between 2007 and 2008 to capture the U.S. sub-prime mortgage financial crisis.

	Median Correlation	Volatility	Capitalization
N	99	99	99
R-Square	0.7679	0.5924	0.9182
Adj R-Sq	0.7579	0.5749	0.9156
Intercept	0.34049**	25.89456**	-8.68225**
	(8.84)	(11.34)	(-3.23)
Trend	0.00003**	0.00356**	0.0017**
	(5.36)	(10.11)	(4.26)
Size	-0.01987**	-1.47304**	0.79058**
	(-6.86)	(-8.57)	(4.03)
EQBK	-0.38686**	-2.03173	
	(-4.59)	(-0.41)	
DUM07_08	-0.01104**	-0.1319	0.95856**
	(-4.14)	(-0.83)	(5.14)

Note:
*** and ** statistically significant at the 5% and 1% level respectively.**
EQBK is not included in the regression analysis on capitalization to avoid the problem of endogeneity.

5.2. Systemic risk indices

Through the application of Monte Carlo simulation, the systemic risk indices SIV and SIN are calculated. I generate 9 values of the indices SIV and SIN in every quarter, corresponding to fraction values of 5%, 10% and 15% and number of simulations of 1 million, 2 million and 4 million.

Table 5.4 displays the probabilities of default with standard errors (in brackets) of the systemic risk indices under the three values for the number of simulations in a random quarter. SIV is the default probability based on bank assets. SIN is the probability that x% of all banks default simultaneously. Note that the standard errors decrease as increase in the number simulations increases, thus indicating the increase in accuracy of the estimates. Because the values for SIN (15%) are equal or very close to 0, it is not presented in Table 5.4 and the subsequent graphs. The results in Table 5.4 show that as the number of simulations increase, the default probabilities associated with SIV and SIN do not change much.

Table 5.4 Examples of systemic risk on assets (SIV) and systemic risk on the number of banks (SIN)

	Number of runs in Monte Carlo simulation		
	1 million	2 million	4 million
SIV (5%)	44.027% (0.016%)	43.813% (0.011%)	43.637% (0.008%)
SIV (10%)	13.801% (0.016%)	13.598% (0.011%)	13.791% (0.008%)
SIV (15%)	0.545% (0.015%)	0.556% (0.010%)	0.557% (0.007%)
SIN (5%)	11.090% (1.029%)	11.390% (0.731%)	11.508% (0.518%)
SIN (10%)	2.240% (1.482%)	2.445% (1.054%)	2.318% (0.743%)

Figure 5.3 and Figure 5.4 display the trends in both systemic risk indices for different fraction values. From the graphs, we find that the indices capture the jump up during the period from 1995 to 1997.

Figure 5.3 Probabilities that banks with total assets of more than 5%, 10% and 20% of all assets held by banks become bankrupt within the next two quarters (SIV)

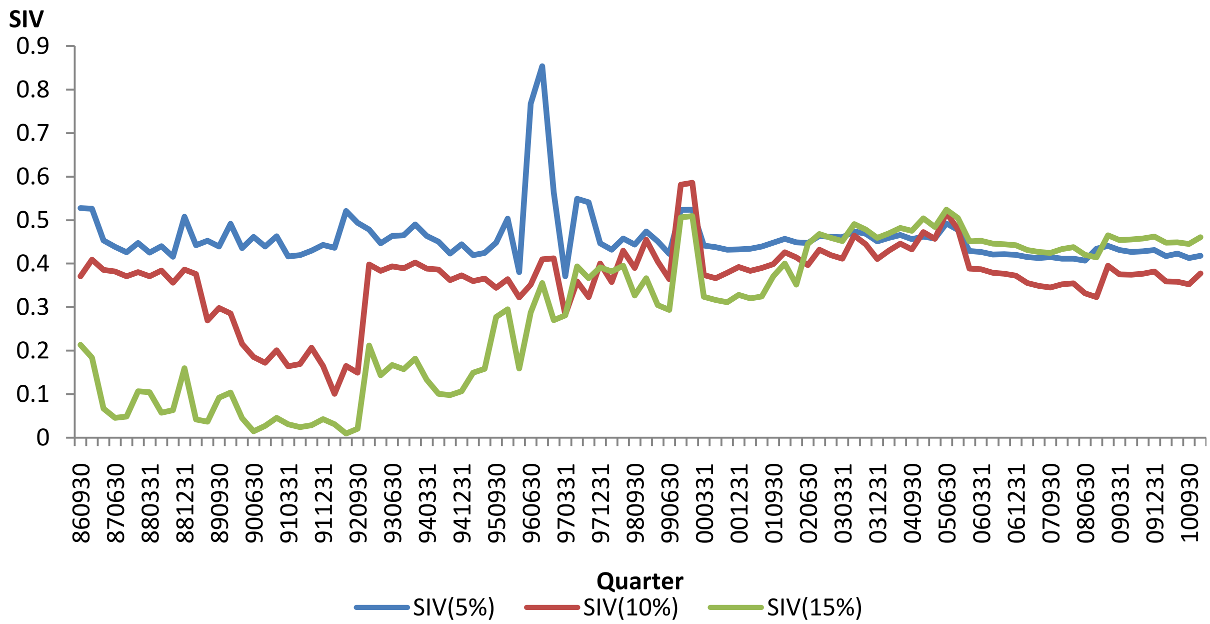
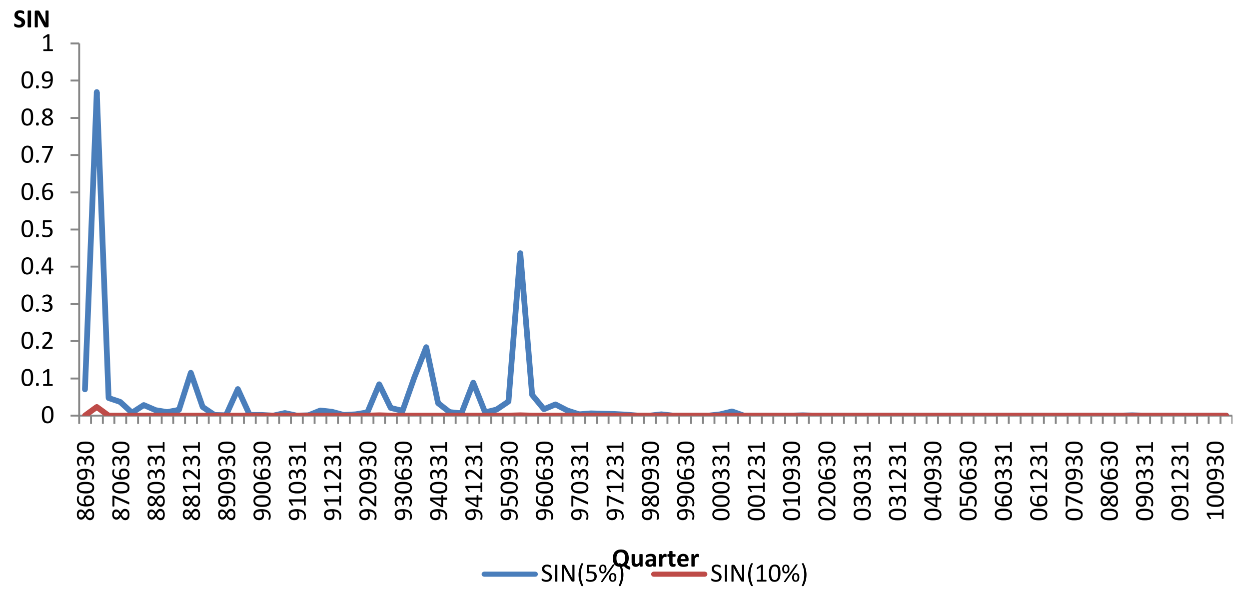


Figure 5.4 Probabilities that more than 5%, 10% and 20% of all banks become bankrupt within the next two quarters (SIN)



5.3. Relationship between the systemic risk indices, the systemic and the bank specific factors

It may not be relevant to just look at the dynamic of the two kinds of systemic risk indices. For a researcher's perspective, it is necessary to check whether these indices can demonstrate systemic risk in the U.S. banking industry. Based on section 4.2.2, two categories of explanatory variables can be established. The first category is related to systemic risk factors including the median correlation of market value of assets, the median volatility of assets and the median capitalization. The second group consists of three bank specific factors: time trend, size, and the ratio of equity to total assets. Then, the regression analyses of SIV and SIN on the two groups of factors as described by equations (26) and (27) are conducted to investigate the relationship between the systemic risk indexes and the two groups of factors.

Table 5.5 shows the results of the regression analyses which explain the indices based on the systemic factors and the dummy variable which captures the effect of implementation of Basel I.

Confirming hypothesis 7, both volatility and capitalization are significantly related to the risk indices. The positive relation between DUM89_94 and SIV indicates that the effect of implementation of Basel I is to significantly increase systemic risk. It is surprising to observe the contrasting relationship between the median correlations and the indexes. As the interconnectedness between banks increases, the median correlation should be lower; however, this variable is negatively related to the SIN index.

Table 5.5
Results obtained from the panel regression explaining SIV and SIN at 5%. The explanatory variables are the median correlation, volatility, capitalization, and the dummy variable which captures the effect of implementation of Basel I (DUM89_94).

	SIV	SIN
N	98	98
R-Square	0.6724	0.1707
Intercept	0.36505**	0.00423
	(5.92)	(0.05)
Median Correlation	0.01269	-2.36614*
	(0.02)	(-2.26)
Volatility	0.02466*	0.03399*
	(2.22)	(2.27)
Capitalization	-0.04286**	-0.03257**
	(-7.59)	(-4.28)
DUM89_94	0.05999**	0.000214
	(3.27)	(0.01)

Note:
*** and ** indicate statistical significance at the 5% and 10% level.**

In comparison, Table 5.6 displays the relationship between the indices of systemic risk and bank specific factors as represented by equations (26) and (27). Only bank size is statistically significantly related to SIV and SIN. The negative coefficients of size indicate that larger banks contribute less to systemic risk. The dummy variable is positively related to SIV and negatively to SIN. Thus, the effect of the implementation of Basel I is to increase the probability that a certain portion of bank assets will be in default, but decreases the probability that a certain number of banks will be in default.

Table 5.6
Results obtained from the panel regression explaining SIV and SIN at 5%. The explanatory variables are trend, size, EQBK, and the dummy variable which captures the effect of implementation of Basel I (DUM89_94).

	SIV	SIN
N	98	98
R-Square	0.7085	0.1343
Intercept	1.74432**	1.23928*
	(5.37)	(2.62)
Trend	5.83E-06	0.000102
	(0.12)	(1.50)
Size	-0.10062**	-0.08175*
	(-4.24)	(-2.36)
EQBK	0.78266	-0.55516
	(1.07)	(-0.52)
DUM89_94	0.03813*	-0.05755*
	(2.44)	(-2.53)

Note:
*** and ** indicate statistical significance at the 5% and 10% level.**

Table 5.7 shows the results of the regression of the indices of systemic risk on the systemic factors, as well as the dummy variable which captures the effect of the subprime mortgage crisis, as represented by equations (28) and (29). The coefficients of volatility and capitalization confirm hypothesis 7; however, median correlation still is positively related to SIV and negatively to SIN. The results also indicate the significant positive relation between the dummy variable and SIV, which means that during this financial crisis, the systemic risk increases.

Table 5.7
Results obtained from the panel regression explaining SIV and SIN at 5%. The explanatory variables are the median correlation, volatility, capitalization, and the dummy variable which captures the effect of the sub-prime mortgage crisis of 2007 and 2008 (DUM07_08).

	SIV	SIN
N	98	98
R-Square	0.6498	0.1729
Intercept	0.40331**	0.00995
	(6.31)	(0.12)
Median Correlation	1.71143*	-2.32024*
	(2.70)	(-2.82)
Volatility	0.01398	0.03351*
	(1.26)	(2.32)
Capitalization	-0.04421**	-0.0339**
	(-7.22)	(-4.26)
DUM07_08	0.04967*	0.01616
	(2.00)	(0.50)

Note:
*** and ** indicate statistical significance at the 5% and 10% level.**

The results of the regression of the indices of systemic risk on the bank specific factors as well as the dummy variable which captures the effect of the subprime mortgage crisis, as represented by regression equations (30) and (31) are shown in Table 5.8. We note that only bank size has a significant negative relationship with both systemic risk indexes. In the regression model of SIV, the dummy variable has a positive coefficient that is significant at the 5% level. This demonstrates that during the financial crisis, the default probability of bank assets increased.

Table 5.8
Results obtained from the panel regression explaining SIV and SIN at 5%. The explanatory variables are trend, size, EQBK, and the dummy variable which captures the effect of the sub-prime mortgage crisis of 2007 and 2008 (DUM07_08).

	SIV	SIN
N	98	98
R-Square	0.6903	0.0749
Intercept	2.02794**	0.84117**
	(6.33)	(6.33)
Trend	4.04E-05	5.89E-05
	(0.82)	(0.82)
Size	-0.1157**	-0.06109*
	(-4.80)	(-1.73)
EQBK	0.10665	0.44003
	(0.15)	(0.43)
DUM07_08	-0.00822	0.000259
	(-0.37)	(0.01)

Note:
*** and ** indicate statistical significance at the 5% and 10% level.**

Chapter 6. Conclusion

In this thesis, I form two systemic risk indexes to investigate the financial health and stability of the U.S. banking industry from 1986 to 2010. These two indices include the default probability based on bank assets (SIV) and the default probability based on the number of banks (SIN). The target sample consists of 100 U.S. commercial banks. An important input to measurement of the systematic risk indexes is the market value of assets, which is estimated by the contingent claims analysis of Merton (1973) and the maximum likelihood estimation method developed by Duan (1994). With the market value of assets, Monte Carlo simulation is applied to form these two systemic risk indices.

In the regression analysis for systemic and bank specific factors, the dummy variable DUM89_94 is positively related to the median correlation of assets and negatively related to the volatility of assets, which means the effect of Basel I improves the median correlation and reduces the volatility. This implies that the shift of bank investment from riskier financial markets to government securities caused by the new risk based capital standards in Basel I did reduce volatility; however, it also makes bank investment more concentrated in a few markets which will simulate the correlation of banks' assets and increase the probability of simultaneous default. Thus the implementation of Basel I does not improve the stability of the U.S. banking industry. The effect of implementation of Basel I reduces the systemic volatility, but cannot completely control systemic risk due to the stronger correlation among the banks' assets. This conclusion is also confirmed by the results of the regression analysis for the systemic risk indices on systemic factors, in which the effect of Basel I does not restrain systemic risk.

The dummy variable capturing the effect of the U.S. sub-prime mortgage financial crisis in 2007 – 2008 presents a significantly positive relation with SIV, which indicates that the systemic risk in the U.S. banking system increases during this financial crisis. This confirms the hypothesis 2 and this financial crisis contributes to the systemic risk of the U.S. banking industry.

The regression analyses of the systemic risk indices on systemic and bank specific factors indicate that most systemic factors including the median correlation of bank assets, the volatility of assets and the capitalization ratio, are statistically significantly related to the risk indices. In contrast, of the bank specific factors, only bank size is significantly related to both indexes. This confirms that the systemic factors perform better than the bank specific factors in explaining the measures of systemic risk. This result is also consistent with the point suggested by Eisenburg and Noe (2001) who state that the risk caused by bank specific factors can be diversified through portfolio diversification. Thus, in an established financial system like the U.S. banking industry, the bank specific factors do not have strong explanatory power for the stability of the entire system.

In summary, the systemic risk indices SIV and SIN do indicate the financial health of the U.S. banking system. According to the results of the regression analysis, volatility and capitalization have strong explanatory power for the systemic risk indices. However, the median correlation only has a moderate influence on SIV. Thus, the index SIV may perform better than SIN in demonstrating the stability of the entire system.

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