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BANKING CRISIS AND CYCLIC SHOCKS: A PERSPECTIVE ON VOLATILITY CLUSTERING

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ABSTRACT

Typical systemic risk measurement barely captures the dynamic risk characteristics of the entire banking system. Experience from past financial crises shows, major indicators in financial markets have clustered volatility during periods of economic downturns. This study focuses on the overall profile of the commercial banking sector. The Ratio of Adjusted Weighted Estimated Loss is introduced as an indicator of banking crisis to analyze volatility clustering in a system-wide perspective. The results show that crises indicator volatility tends to cluster together when distress signals begin to appear in the market. A leverage effect is also presented in the results when applying the EGARCH model. Analysis of the effect of cyclic shocks discusses the process of risk transfer from exogenous shocks to endogenous contagion. The results have implications for a better understanding of the relationship between business cycle and banking crises.

JEL: C32, E32, G01, G21

KEYWORDS: EGARCH, Volatility Clustering, Cyclic Shocks, Leverage Effect

INTRODUCTION

Business models of the entire banking industry have undergone development for decades. But banking failures happened occasionally, and innovation with securitized products was a major driving force in the recent financial crisis. These innovations also have tremendous impact on systemic credit risk and reveals the potential for instability. Similarly, regulatory actions are slow and not strong enough to identify and manage the risk on the eve of a system-wide crisis. Historical experience shows that shocks from macroeconomic factors can cause the collapse of the financial system. Under typical circumstances, systemic risk results from two major sources: exogenous shocks due to the fluctuations of macroeconomic variables and internal contagion processes within the system. It is intuitive to hypothesize the mechanism of the occurrence of banking crisis as follows:

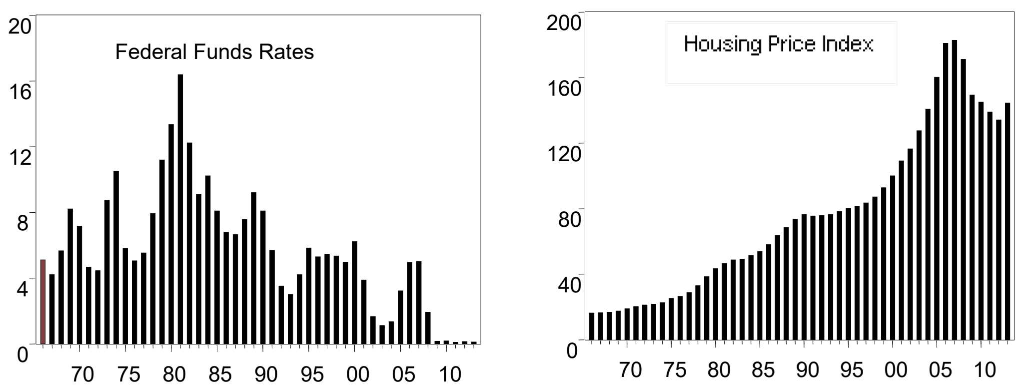
The first stage: Exogenous shocks cyclically give rise to volatility of both commodity prices and capital costs including interest rate uncertainty and the impact on the solvency of financial institutions. This early phase is referred to as out-of-system shocks.

The second stage: A system-wide crisis is caused by endogenous contagion within the financial sector which exacerbates the recession.

Shocks including interest rate fluctuations and deregulation are typically considered major determinants of the savings and loans crisis during the 1980s. As deregulation measures progressed in the 1990s, securitization, a profitable businesses, brought the real estate market to the bubble that ultimately burst. As the banking crisis spread, the system as a whole did not recover promptly from the downward trend. A subsequent in-system contagion process among counterparty institutions occurred which resulted in recession in other sectors. Figure 1 shows the Federal Funds Rate and Housing Price Index from 1966 through 2013.

This study seeks to deepen understanding of the characteristics of systemic risk in banking. This study focuses on system-wide dynamic features of how systemic risk, driven by macroeconomic shocks, is created and transferred through the mechanism of commercial banking. The first objective of this paper is to investigate volatility clustering of banking crises by using a GARCH model. The second mission is to describe how exogenous sources of triggers have affected the banking system and eventually caused a crisis. The rest of this paper is structured as follows: The next section presents the literature review. Then I discuss the methodology and data and report the results of clustering estimation and robustness tests. The next section presents the empirical results of estimation with cyclic shocks. The last section concludes this study.

Figure 1: Federal Funds Rate and U.S. Housing Price Index 1966-2013



This figure shows the Federal Funds Rate and the housing price index from 1966 to 2013; the data source is from Federal Reserve Bank of St. Louis and S&P/Case-Shiller Home Price Indices respectively

LITERATURE REVIEW

Interactions among institutions can cause risk transfer and default contagion through the system. These interactions can also result in contagions from both asset prices and business counterparties (Staum, 2011). Theoretical frameworks of modeling counterparty risk are developed to detect the correlations when a firm's default could lead to another firm's distress (Davis and Lo, 2001; Jarrow and Yu, 2001). Under certain circumstances, banks respond homogeneously to macroeconomic volatilities (Calmès and Théoret, 2014). Nontraditional businesses of banks are more sensitive to the volatility of macroeconomic variables (Lukas and Stokey, 2011). Exogenous shocks may distort the information transfer and thus force financial institutions to reallocate their portfolios of assets (Bernanke and Gertler, 1989). Evidence shows that system-wide uncertainty will cause dispersion in loan-to-asset ratios among affected institutions (Baum et al, 2009). Moreover, exogenous sources of shocks could be created by monetary policy and banks with less liquid assets will be affected more severely (Kashyap and Stein, 2000). Internal dispersion will further aggregate damage to the system. Another finding shows that non-systemic features represent the major component of a firm's risk (Campbell et al., 2001).

Methods for measuring systemic risk in the banking industry are developed from diversified angles. Value at risk (VaR) is widely applied as a measure of systemic risk. The measurement CoVaR, as an extension, is applied to assess the marginal risk of each individual institution (Adrian and Brunnermeier, 2016). Expected shortfall is another frequently used framework in estimating risk and has been developed and derived into various forms such as systemic expected shortfall and marginal expected shortfall (Tarashev et al, 2009; Acharya et al., 2017). Expected shortfall, shows that interconnectedness among banks plays a significant role in systemic risk aggregation (Drehmann and Tarashev, 2013). An exogenous framework, through the application of Default Intensity Model (DIM), is employed in the analysis. In this case, the properties of credit risk are formulated as the insurance price against the risk faced by financial institutions (Huang et al., 2009). Other research shows that systemic risk can be measured by defining an event that individual banks fail simultaneously. In this case, there is no clear boundary when the combined failures of individual banks become a systemic disaster (Lehar, 2005). Systemic risk is also defined as a failure-based measure by calculating the conditional probability of bank failures in a large portion of the whole financial intermediaries (Giesecke and Kim, 2011). Some researchers investigate early warning system based on different theoretical foundations to predict financial crises (Gramlich et al, 2010 and Illing and Liu, 2006).

DATA AND METHODOLOGY

A dataset of commercial bank failures is constructed from FDIC Historical Statistics on Banking Failures and Assistance Transactions. Data covers the period from 1986 to 2013. All 1722 bank observations are incorporated into the dataset. The variable Total Assets and Estimated Loss of each failed institution is collected for the calculation of a yearly indicator of banking crisis. The data of total assets of all commercial banks is collected from the Federal Reserve Board (FRB) Assets and Liabilities of Commercial Banks in the United States - H.8. The indicator of banking crisis is measured by defining the ratio of adjusted weighted estimated-loss (termed *rawel*). The *rawel* is devised to measure the level of overall loss in the banking system. The form of *rawel* is as follows:

$$rawel_t = \frac{safb_t}{tacb_t} \times \left(\sum_{i=1}^{k}(ar_{it} \times \frac{el_{it}}{aib_{it}})\right) \tag{1}$$

Where k indicates the number of failed banks in one observation year t; *safb* denotes the aggregate assets of failed banks in year t and *tacb* is the total assets of all commercial banks in the same year. The whole term in the parenthesis represents the ratio of weighted estimated-loss before adjustment for each year, *el* is the amount of estimated loss for each failed bank, and *aib* indicates the total assets of the individual bank i. The term *ar* represents the weight of bank i's assets in aggregate assets of all failed banks. The regression imputation method is applied in solving the zero observations. Descriptive statistics are presented in Table 1.

The volatility of *rawel* is assumed as the proxy of the volatility of banking crisis. It can be tested for time-varying volatility clustering under the framework of Generalized Autoregressive Conditional Heteroskedasticity (Bollerslev, 1986). A typical form of GARCH is presented in the following equations:

$$r_t = \varphi x' + \varepsilon_t \tag{2}$$

$$\sigma_t^2 = \beta_0 v + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 \tag{3}$$

Where the conditional heteroskedasticity is the function of three components including long-term mean, square of stochastic error and lagged term variance. Eifferent weights have been allocated for each term as coefficients. The limitation on the coefficients in GARCH can be relieved in an Exponential GARCH model (Nelson, 1991), which is specified as follows:

$$log(\sigma_t^2) = \beta_0 + \beta_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta_2 \log(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4}$$

The leverage effect becomes exponential after taking logarithmic volatility into consideration. The coefficient γ follows the null hypothesis that the impact of informational shocks will be symmetric if it's equal to zero, otherwise, asymmetric information effect exists with a positive coefficient indicating more powerful upward information. I construct the mean equation with one term lagged, where equation (5) is introduced with only lagged terms, and equation (6) includes exogenous variables.

$$0rawel_t^{lag} = \beta_0 + \beta_1 rawel_{t-1} + \varepsilon_t \tag{5}$$

$$rawel_t^{ex} = \beta_0 + \beta_1 ffr_t + \beta_2 niir_t + \beta_3 ncf_t + \beta_4 sglr_t + \beta_5 rawel_{t-1} e^{1+hpr_t} + \varepsilon_t \tag{6}$$

Table 1: Descriptive Statistics

Year	No. of Bank Failures	Mean of TA	Mean of EL	S.D. of EL	TA of Commercial Banking
1986	144	56.80	12.28	24.92	2928.85
1987	201	38.30	9.75	17.05	2986.59
1988	280	192.49	24.71	132.80	3116.30
1989	206	136.19	28.69	130.17	3283.83
1990	159	67.00	12.07	27.81	3369.56
1991	108	407.49	26.63	76.42	3413.49
1992	99	156.60	14.94	31.16	3486.13
1993	42	73.13	12.88	15.63	3684.87
1994	11	83.61	14.76	15.15	3984.65
1995	6	133.69	14.08	9.07	4285.28
1996	5	40.01	7.74	5.03	4551.34
1997	1	27.92	5.03	-	4983.85
1998	3	96.75	74.23	124.71	5400.19
1999	7	217.60	98.14	212.80	5687.97
2000	6	63.11	5.20	6.23	6192.25
2001	3	18.77	1.93	1.97	6491.79
2002	10	282.11	46.29	56.63	7008.63
2003	2	469.42	30.98	25.73	7521.94
2004	3	52.23	1.96	1.47	8319.42
2005	0	-	-	-	8936.00
2006	0	-	-	-	9991.52
2007	1	125.36	29.38	-	11073.97
2008	23	56477.39	250.23	295.68	12208.27
2009	126	14915.72	185.36	455.62	11728.64
2010	129	454.31	99.04	126.36	11986.13
2011	84	323.97	78.72	72.69	12573.88
2012	40	229.90	54.11	63.28	13318.70
2013	23	258.74	50.59	129.75	13600.76
Total	1722	2008.41	43.73	159.74	

This table shows descriptive statistics of the sampled data set of failed banks from 1986 to 2013. The third column reports the mean total assets in millions of all failed banks in one sample year. The fourth column reports the mean estimated loss in millions of all failed banks during the same year. The fifth column reports the standard deviation of estimated loss in each year. The sixth column presents total assets in billions of all commercial banks in the corresponding year.

In equation (6), variable *ffr* represents the federal funds rate; *sglr* denotes the proportion of gains and losses of securities in the total value of investment securities in commercial banks, and *niir* is the proportion of net interest income in total interest income; *ncf* represents logarithmic ratio of net charge-offs to net loans and leases; the lagged term is adjusted by multiplying the exponential growth rate of housing price to detect the combined impact from the emphasis on the housing market, where *hpr* is the growth rate of a nationwide housing price index. This term will be substituted by *multi* in the empirical section. Housing price data is selected from the S&P/Case-Shiller U.S. National Home Price Index. The variable *ffr* is employed as the exogenous control variable in this initial setting. The housing price is considered another control variable as well as federal funds rate. The effects these variables brings to the banking crisis measurement will be discussed as a comparison in the robustness test. For the tests of exogenous shocks, I define the ratio of failed assets (termed as *rfa*) as the proxy for banking crisis in a longer time span because the data of the estimated loss of each bank is only available since 1986. The *rfa* is expressed as follows:

$$rfa = \frac{Total\ Assets\ of\ Failed\ Banks}{Total\ Assets\ of\ the\ Banking\ System} \tag{7}$$

Total assets of failed banks are not the exact representative of the magnitude of the systemic failure but could be considered as "contaminated" assets which would experience rapid depreciation. Federal funds rate and housing price index are assumed driving factors of the exogenous shocks and selected as proxy measures. To detect the relationship between out-of-system shocks and system-wide indicators, Vector Autoregression is employed to investigate the effects. A restricted form of VAR is also applied in the analysis and could provide an error correction term to express the long-term relationship.

Clustering Estimation

Table 2 shows the best fitted characterization comes from GARCH (1, 1). The ratio series after revision shows more robustness and goodness of fit in both GARCH and EGARCH tests. By comparing general conditional variance with exponential conditional variance, explanatory power is not presented explicitly with the limited hypothesis of GARCH model despite the significance of the coefficients. The results imply the GARCH model is not convergent. In contrast, the EGARCH model provides a better interpretation of the behavior of volatility. The EGARCH results are essentially unchanged and no asymmetric information effect has been detected in this setting. It implies that positive shocks and negative shocks are not behaving in an unbalanced fashion implying that one source of volatility cannot dominate the other.

Table 2: Tests of Volatility Clustering

	$rawel_t^{lag}$		$re\_rawel_t^{lag}$		$rawel_t^{ex}$		$re\_rawel_t^{ex}$	
	(a)	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
Constant	0.0519	0.0011	0.0335	-0.0006	4.8104***	1.9194***	4.7956***	1.3608***
	(1.6652)	(0.1571)	(0.5565)	(-0.0145)	(3.5522)	(4.4131)	(6.6957)	(3.7056)
$rawel_{t-1}$	0.6014***	0.5908***	0.6056***	0.6512***				
	(6.1787)	(6.9872)	(5.2243)	(4.3179)				
ffr					-	-	-0.3632***	-
					0.3659***	0.1383***	(-6.8023)	0.1007***
					(-3.7121)	(-4.1525)		(-3.7339)
niir					-	-	-5.3561***	-
					5.3012***	2.1960***	(-6.0465)	1.5478***
					(-3.1159)	(-4.5411)		(-3.6963)
ncf					0.5501***	0.1261	0.5284***	0.1139**
					(4.8700)	(1.5136)	(5.3508)	(2.3857)
sglr					-	-	-	-
					119.26***	42.995***	107.775***	29.496***
					(-7.6116)	(-3.6746)	(-5.7105)	(-3.6029)
multi					0.0872	0.0468	0.0607	0.0400*
					(1.2896)	(1.2038)	(1.3139)	(1.8956)
β_0	-0.0021	0.6780***	-0.0029**	0.4523***	0.0088	-	0.0029	-
	(-1.5064)	(4.5646)	(-2.3433)	(3.5064)	(0.7469)	5.6924***	(0.5487)	6.2956***
						(-3.8775)		(-6.4005)
β_1	-	-	-	-	1.6605**	3.3896***	2.3440**	3.5470***
	0.1183***	0.9963***	0.1533***	0.6195***	(2.2217)	(4.4024)	(2.1959)	(6.3476)
	(-5.3575)	(-5.3302)	(-4.5782)	(-5.2525)				
β_2	1.3896***	1.0269***	1.4744***	1.0231***	-0.0157	0.3926	-0.0097	0.3916*
	(12.792)	(26.196)	(11.659)	(34.240)	(-0.1031)	(0.9479)	(-0.4113)	(1.6463)

This table shows GARCH tests of volatility clustering. The model of mean equation is specified as follows: $rawel_t^{lag} = \beta_0 + \beta_1 rawel_{t-1} + \varepsilon_t$ *and* $rawel_t^{ex} = \beta_0 + \beta_1 ffr_t + \beta_2 niir_t + \beta_3 ncf_t + \beta_4 sglr_t + \beta_5 rawel_{t-1} e^{1+hpr_t} + \varepsilon_t$ *Column (a) and (b) show the results of GARCH test and EGARCH test respectively. Coefficient* γ *representing the effect of asymmetric information is zero in EGARCH model so it is not presented in this table. The figures in the parenthesis are z-statistics. The term multi represents the interaction effect between the lag term of rawel and the exponential form of housing price index. ***, **, * are significant at the 1%, 5%, and 10% level respectively;*

Robustness Test

To test the robustness of the model, reconsideration of correlations between variables has been conducted on a hypothesized basis that shocks from interest rate and real estate markets are major contributors to the volatility clustering of banking failures. The federal funds rate *ffr*, therefore, is put into the model with the same role as exponential growth rate of housing price index. By switching different control variables, the fit of goodness and compatibility is specified in the following Table 3.

Table 3: Robustness Test (1)

	$rawel_t^{ex}$		$re\_rawel_t^{ex}$	
	(a)	**(b)**	**(a)**	**(b)**
Constant	2.3536***	2.3270***	2.3302*	2.0194**
	(3.1458)	(15.4783)	(2.1330)	(4.6280)
exp_hpi	-1.0762***	-0.9727***	-1.0786**	-0.7911**
	(-3.9608)	(-15.0410)	(-2.7514)	(-4.7317)
niir	1.6412***	0.9130***	1.7223**	0.5274*
	(3.4790)	(6.6983)	(4.2427)	(2.2224)
ncf	0.4708***	0.2502***	0.5886**	0.1928**
	(4.6178)	(7.1481)	(5.8040)	(3.4361)
sglr	-	-16.9642***	-72.5026**	-18.8044**
	61.8636***	(-3.7693)	(-3.3327)	(-3.2016)
	(-2.8754)			
*Rewel_lag**	0.07017	0.0717*	0.0483	0.0141
ffr_ lag	(0.8367)	(1.6617)	(0.3527)	(0.3429)
β_0	0.0191	-5.9214***	0.0342	-4.6864***
	(0.9141)	(-4.6733)	(0.7765)	(-3.2410)
β_1	1.9865	3.7706*	1.3227	4.4822***
	(1.6170)	(4.5625)	(1.3325)	(3.9159)
β_2	-0.3198	0.3102	-0.4265	0.8283**
	(-1.0017)	(1.3824)	(-0.6679)	(2.4284)

This table shows the robustness test of volatility clustering with exogenous variables. The model of mean equation is specified as follows: $rawel_t^{ex} = \beta_0 + \beta_1 e^{1+hpr_t}{}_t + \beta_2 niir_t + \beta_3 ncf_t + \beta_4 sglr_t + \beta_5 rawel_{t-1} ffr + \varepsilon_t$*. Column (a) and (b) shows the results of GARCH test and EGARCH test respectively. Coefficient* γ *representing the effect of asymmetric information is zero in this model so it is not presented in this table. The figures in the parenthesis are z-statistics. The lag term of ffr instead of hpi is included in the interaction term. ***, **, * are significant at the 1%, 5%, and 10% level respectively;*

The result is basically unchanged and the exponential GARCH test is much better performing than the original GARCH as shown in Table 4. Similar to the result of *rawel* previously discussed, the revised version of variable has shown marginally more power of explanation but not a dominant one. The uncertainty of housing prices will results in a negative effect to the banking system as well as the federal funds rate. But the effect magnitude of housing price is greater than *ffr* and forms a more straightforward facilitator to the crisis. The standard deviation *devr* of all ratios of estimated losses in each sampled year is another estimator that can interpret the extent of dispersion among failed commercial banks. The calculation takes *ar* as weights. However, it is clearly shown that the standard deviation overestimates the systemic importance during some periods with less banking failure events, such as from 1998 to 1999, and thus a multiplier which indicates the relative systemic importance for each cross section is added to the measure:

$$devr_t = \frac{k}{\bar{k}} \sqrt{\sum_{i=1}^{k} ar_{it} \times (el_{it} - \overline{el}_t)^2} \tag{8}$$

Where $\bar{k}$ indicates the mean of the failure counts of the sampled period. This measure gives rise to a general assessment of the institution-wide dispersion effect. The result implies that exponential the GARCH model can also capture volatility clustering. On the other hand, the lag equation shows less explanatory capacity in both GARCH and EGARCH tests. In the setting of exponential equation, all coefficients are significant at least at the confidence level of 90%.

Table 4: Robustness Test (2)

	$devr_t^{lag}$		$devr_t^{ex}$		
	(a)	**(b)**	**(a)**	**(b)**	**(c)**
Constant	1.2007	-0.0000	0.0661	0.1891***	-0.1195***
	(0.2680)	(-0.0001)	(0.4493)	(4.2982)	(-6.4608)
ffr/dhpi			-0.0093	-0.0127***	-0.0025***
			(-0.8244)	(-4.3807)	(-7.2359)
niir			-0.0564	-0.2444***	0.2238***
			(-0.3161)	(-4.4162)	(7.5895)
ncf			0.1369***	0.0230***	0.0210*
			(3.6190)	(5.1938)	(1.7735)
sglr			1.5089	0.3570	5.4871***
			(0.6161)	(0.9136)	(6.5183)
devr_lag/	0.7516**	0.7767***	0.2779***	0.2771***	0.1013***
multi	(2.2349)	(16.1403)	(7.5956)	(82.8583)	(57.2894)
β_0	15.1146	-0.1232	0.0010	-5.7881***	-5.6948***
	(0.3735)	(-0.3732)	(1.3134)	(-4.7758)	(-4.2701)
β_1	-0.0840***	-0.8464***	0.5515**	6.5645***	5.3781***
	(-5.8027)	(-6.5162)	(2.1650)	(5.3868)	(5.1643)
β_2	0.5802	0.8865***	-0.0312	0.8420***	0.7656**
	(0.5600)	(21.7636)	(-0.2390)	(3.2382)	(2.3290)
γ					-1.7144*
					(-1.9043)

*This table shows the second robustness test with dispersion. Column (a) and (b) shows the results of GARCH test and EGARCH test respectively. This test contains exogenous equations and one additional test for asymmetric information effect presented in column (c). The denotation ffr applies to column (a) and (b) in the exogenous equations; the term dhpi regarded as the difference of hpi applies to column (c); The denotation devr_lag applies to the two lag equations and the multi term indicates exp_hpi*devr_lag for columns (a) and (b) and ffr_lag*devr_ lag for the column (c) correspondingly; ***, **, * are significant at the 1%, 5%, and 10% level respectively;*

More evidently, asymmetric impacts of information are detected in (c) column where $\beta2+\gamma=3.6637$ when $\varepsilon>0$ and $\beta2+\gamma=7.0925$ when $\varepsilon<0$. This finding implies that volatility is more sensitive to negative information, and the magnitude of the negative information effect is about twice of the positive information effect.

TESTS OF CYCLIC SHOCKS

Impacts from Exogenous Fluctuations

Long-term correlations between different time series can be investigated by the co-integration test. The three chosen financial ratios *ncfr*, *niir* and *sglr* are modeled as in-system variables in the VAR analysis with *ffr* and hpi as shock variables out of system. By testing the unit root of each variable under Augmented Dickey-Fuller criteria, the result, shown in Table 5, illustrates variables *rfa*, *ncfr*, *sglr*, *ffr* and hpi are stationary under at least 95% confidence level. The only variable not stationary is *niir* so that it is substituted by *niirc* after being processed by the Hodrick-Prescott filter.

Table 5: Unit Root Test

	rfa	*ncfr*	*niirc*	*sglr*	*ffr*	*hpi*
t-statistic	-4.7170	-5.5159	-7.2761	-3.9964	-3.9146	-4.1118
Prob	0.0004	0.0002	0.0000	0.0031	0.0192	0.0117

This table reports the results of unit root test. The variables rfa, ncfr, niirc, sglr, ffr and hpi represent the ratio of failed assets, ratio of net charge-offs, proportion of net interest income in total interest income, proportion of gains and losses of securities in the total value of investment securities, federal funds rate and housing price index respectively. Every variable is stationary at the significance of 5%

Table 6 presents the results of the co-integration test. As it is specified in Section 2, I have conducted co-integration test for every pair of variables in the hypothesized contagion systems. Both the Trace statistic and Max-Eigen statistic indicate at least one co-integration equation exists in each pair of variables. The same implication applies to the corresponding pairs with one term lagged *rfa*. Exceptions are shown in the correlation with *ncfr* in the hypothesis of none co-integration equations, where trace and max-eigen statistics present different results.

Table 6: Co-integration Test

Panel A				**Panel B**			
rfa	**No. of CE(s)**	**Trace (Max-Eigen)**	**Prob**	rfa_{t-1}	**No. of CE(s)**	**Trace (Max-Eigen)**	**Prob**
$ncfr$	None	21.9833 (12.7277)	0.0046(0.0862)	$ncfr$	None	16.3688(10.4074)	0.0369(0.1865)
	At most 1	9.2556 (9.2556)	0.0023(0.0023)		At most 1	5.9614(5.9614)	0.0146(0.0146)
$sglr$	None	25.5999(16.5549)	0.0011(0.0213)	$sglr$	None	36.1638(21.7703)	0.0000(0.0027)
	At most 1	9.0450(9.0450)	0.0026(0.0026)		At most 1	14.3935(14.3935)	0.0001(0.0001)
$niirc$	None	43.3106(33.5822)	0.0000(0.0000)	$niirc$	None	47.0994(37.1161)	0.0000(0.0000)
	At most 1	9.7284(9.7284)	0.0018(0.0018)		At most 1	9.9833(9.9833)	0.0016(0.0016)

This table reports co-integration tests to investigate long-term relationships between rfa and the three financial indicators. Johansen methodology is employed in this test for multiple variables. For the purpose of comparison, Panel B presents the co-integration results with the lagged ratio of failed assets. The figures in the parenthesis in the second column of each panel are Max-Eigen statistics.

By identifying the long-term relationship with co-integration test, a restricted Vector Autoregression model, that is, Vector Error Correction Model could be applicable to the analysis. However, it is more reasonable to make a comparison with the unrestricted VAR model so that it is conducted in the exemplified contagion process. The VAR system is specified as follows:

$$\begin{bmatrix} Y \\ X \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} + \boldsymbol{A_1} \begin{bmatrix} Y_{t-1} \\ ffr_{t-1} \end{bmatrix} + \boldsymbol{A_2} \begin{bmatrix} Y_{t-2} \\ ffr_{t-2} \end{bmatrix} + \boldsymbol{A_3} \begin{bmatrix} Y_{t-3} \\ ffr_{t-3} \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (9)$$

Where Y = $[ncfr \quad sglr \quad niirc]^{\mathrm{T}}$ and X = $[ffr \quad hpi]^{\mathrm{T}}$; A_j with j=1,2,3 represents the matrix of parameters; The term $\mathrm{u_i}$ is the stochastic error. The results in Table 7 exhibit the explanatory performance of the coefficients against in-system variables. In terms of the ratio of net charge-offs, housing price produces more explicit impact to the measure. It could be related to traditional exposure to the real estate market and the write-downs of assets proportionally came from fluctuations of housing price. Shocks from interest rate are less significant. The ratio of securities gains and losses reacts evidently to the federal funds rate in recent periods rather than in further lagged periods. The response to the housing market appears to be slow and cannot indicate a direct co-movement in between.

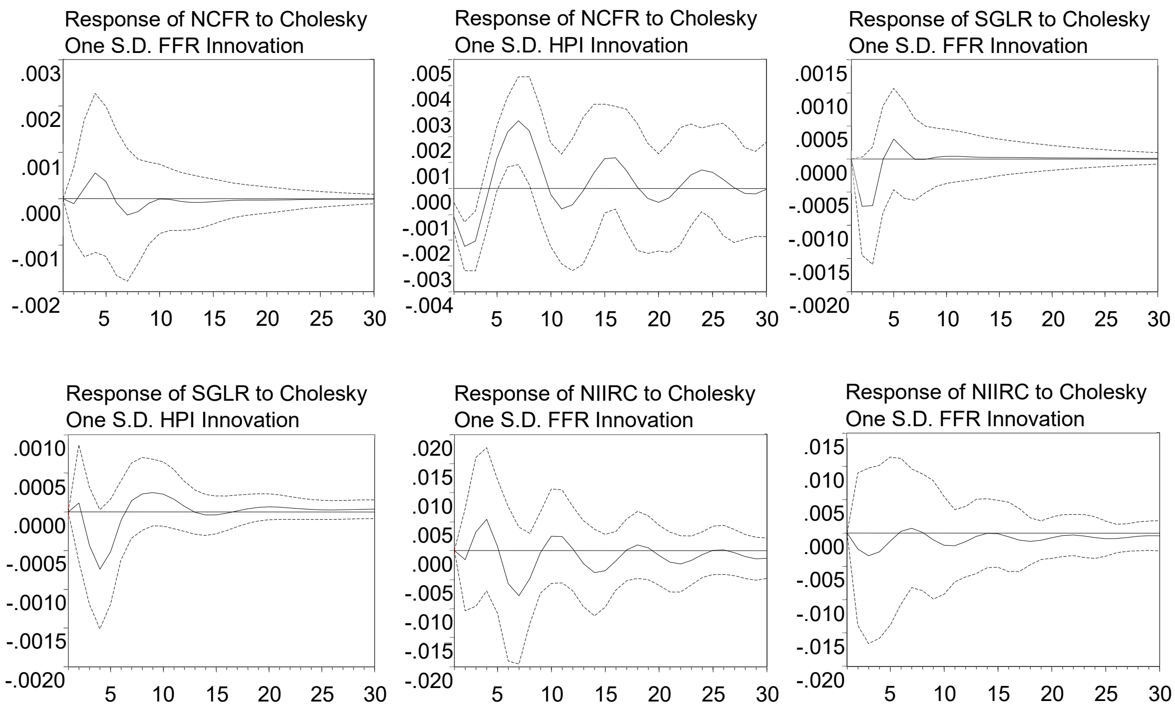
Table 7: Vector Autoregression Results

	$ncfr$	$ncfr_{t-1}$	$sglr$	$sglr_{t-1}$	$niirc$	$niirc_{t-1}$
$constant1$	0.0017	0.0016	0.0005	0.0017**	0.0061	0.0057
	(1.0941)	(1.0989)	(0.6251)	(2.3023)	(0.5664)	(0.6609)
ffr_{t-1}	-0.0001	-0.0004**	-0.0004*	-0.0002**	-0.0014	-0.0123***
	(-0.2721)	(-2.0834)	(-1.9773)	(-2.0284)	(-0.3621)	(-5.1696)
ffr_{t-2}	0.0003	0.0004	0.0003	—	0.0061	0.0156***
	(0.9373)	(1.4935)	(1.0366)	—	(1.0356)	(3.7884)
ffr_{t-3}	-0.0002	-0.0001	0.0001	—	-0.0057	-0.0045
	(-1.1061)	(-0.3759)	(0.3884)	—	(-1.4947)	(-1.4525)
$constant2$	0.0001*	0.0001*	0.0006	0.0004	0.0055	0.0068
	(1.9582)	(1.9818)	(0.8000)	(0.5089)	(0.6209)	(0.7527)
$\mathrm{h}pi_{t-1}$	-0.0003***	-0.0003***	0.0000	0.0001	-0.0007	-0.0008
	(-3.0427)	(-4.4490)	(0.3037)	(1.0148)	(-0.7642)	(-0.9003)
$\mathrm{h}pi_{t-2}$	0.0005**	0.0004***	-0.0002	-0.0002	0.0006	-0.0007
	(2.4515)	(2.9194)	(-1.0214)	(-1.4559)	(0.7004)	(0.8200)
$\mathrm{h}pi_{t-3}$	-0.0000	-0.0001	0.0001	0.0002*	—	—
	(-0.0378)	(-1.0581)	(1.6006)	(1.6956)	—	—
$\mathrm{h}pi_{t-4}$	-0.0002	—	—	—	—	—
	(-1.5887)	—	—	—	—	—

*This table shows the Vector Autoregression results between exogenous shocks and internal financial indicators. The variables ncfr, sglr, niirc, ffr and hpi represent ratio of net charge-offs, proportion of gains and losses of securities in the total value of investment securities, proportion of net interest income in total interest income, federal funds rate and housing price index respectively. ***, **, * are significant at the 1%, 5%, and 10% level respectively.; Each pair under estimation complies with optimal lags criterion*

Impulse responses are presented in Figure 2. Cholesky decomposition method is introduced as the transformation matrix to structure irrelevant error terms. Given an exogenous shock to the system, responses of *ncfr* to *ffr* are approximately positive and then turns to be negative after six periods. However, its response to *hpi* shows a slower process of stabilization. The variable *sglr* responds to *ffr* negatively and the response turns to be positive before stabilizing and the response to *hpi* shows a similar pattern. The net interest income measure *niirc* responds to the shocks from *ffr* in a more volatile way than the response to *hpi*. All the three responses tend to be stable after several fluctuations despite of different horizon of absorbing the impact, which indicates that the impact from exogenous shocks is not permanent to the system.

Figure 2: Impulse Response of NIIRC to Cholesky One S.D. HPI Innovation

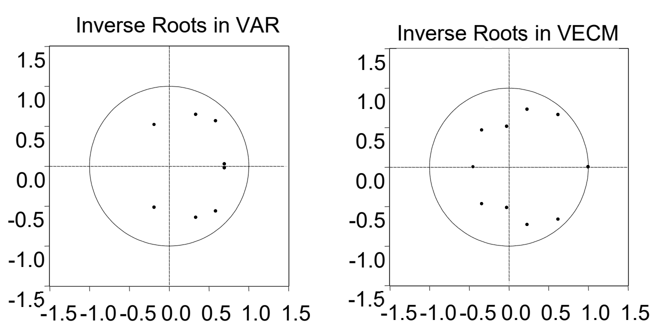


This figure shows the impulse response of each pair of relationship. The variables ncfr, sglr, niirc, ffr and hpi represent ratio of net charge-offs, proportion of gains and losses of securities in the total value of investment securities, proportion of net interest income in total interest income, federal funds rate and housing price index respectively.

Internal Contagion Process

The error correction term is introduced into the system to conduct the comparison between VECM and unrestricted VAR. It can be observed that the VAR system is more stable than the VECM system by testing the inverse roots of AR characteristic polynomial. Figure 3 shows no roots locate outside the unit circle implying that the unrestricted VAR model satisfies the stability condition in each system.

Figure 3: Inverse Roots of AR Characteristic Polynomial



This figure shows the inverse roots of the system of VAR and VECM. The roots in both VAR and VECM locate inside the unit circle.

In Table 8, depicts a comparison between VAR and VECM. The term of the co-integration equation represents the speed of adjustment to equilibrium. The positive coefficients in both columns of VECM show no long-term causality. The results indicate that shocks from the three independent variables to *rfa* will be stabilized due to short-term causality. VECM shows a slightly better explanatory power than unrestricted VAR model in the relationship between *ncfr* and *rfa*.

Table 8: Comparison between VAR and VECM

	Unrestricted VAR		VECM	
	rfa	rfa_{t-1}	$d(rfa)$	$d(rfa_{t-1})$
Co-integration eq.	—	—	0.3162*	0.4263***
	—	—	(1.9787)	(2.7991)
$constant$	0.0107	0.0091	0.0041	0.0024
	(1.0513)	(1.1220)	(1.3108)	((0.7654))
$ncfr_{t-1}$	0.8087	—	-0.3439	—
	(0.2510)	—	(-0.1169)	—
$ncfr_{t-2}$	-5.0982	-1.9585	-4.1400	2.0488
	(-1.1378)	(-0.7287)	(-1.3408)	(0.7311)
$ncfr_{t-3}$	2.8438	1.0648	-4.0255	-6.0628***
	(1.3575)	(0.5997)	(-1.5939)	(-2.6578)
$sglr_{t-1}$	-2.6955	—	-4.7340***	—
	(-1.4229)	—	(-2.7409)	—
$sglr_{t-2}$	7.2869***	-2.9422	2.5319	-5.5855***
	(3.6811)	(-1.6383)	(1.2642)	(-3.2870)
$sglr_{t-3}$	-1.4749	5.5285***	0.2891	2.6551
	(-0.7363)	(3.4191)	(0.1575)	(1.4955)
$niirc_{t-1}$	-0.1027	—	0.3047*	—
	(-0.8935)	—	(1.9763)	—
$niirc_{t-2}$	-0.2305	-0.0930	0.0691	0.2859**
	(-1.4789)	(-1.1472)	(0.4459)	(2.3216)
$niirc_{t-3}$	-0.0290	-0.2674***	-0.0748	0.0070
	(-0.2243)	(-2.8944)	(-0.5639)	(0.0544)

*This table shows a comparison between Vector Autoregression and Vector Error Correction Model. The variables rfa, ncfr, sglr, niirc represent ratio of failed assets, ratio of net charge-offs, proportion of gains and losses of securities in the total value of investment securities, proportion of net interest income in total interest income respectively. ***, **, * are significant at the 1%, 5%, and 10% level respectively; In the VECM system, each independent variable (ncfr,sglr and niir) in the left column represents the difference of the original value.*

The differences of variables *ncfr* and *sglr* show a pattern of consistency in affecting the independent variable *rfa* while this effect does not exist in unrestricted VAR system. It indicates that a longer impact will be created to the ratio of failed assets. Further, these two indicators will not digest the shocks in a short period. Through this process, the volatility from shocks out of the system will be transferred through the mechanism, creating a potential of financial crisis.

CONCLUSION

The goal of this study is to propose a measure of banking crisis to capture dynamic features of systemic risk. Generalized Autoregressive Conditional Heteroskedasticity is employed to portray volatility clustering of the banking crisis measure with the data of bank failures selected from Federal Deposit Insurance Corporation. The Ratio of Adjusted Weighted Estimated Loss is calculated as the indicator of banking crisis, providing a straightforward and proxy-free perspective on the risk factor of systemic risk. The Exponential

GARCH model shows the existence of volatility clustering, which indicates a possibility that in general large losses in the banking sector would be followed by large losses. On the other hand, the GARCH model has weaker explanatory capacity in capturing and characterizing the behavior of volatility. Asymmetric information effect of dispersion degree indicates the banking system will respond more drastically to negative information than positive information. The banking system is more sensitive to weak market confidence than positive information signals.

The Vector Autoregression shows that cyclic shocks diffuse into the system and result in contagion in a time-delaying manner. This risk transmission process leads to fluctuations of the system-wide financial indicator represented by ratio of failed assets. The limitation of this research is that the relatively low frequency of time series may compromise the explanatory power of the GARCH model. However, if the yearly observations are transformed into quarterly or monthly observations, missing data points will be increased and the results could be biased. Future research could be conducted in the direction of integrating the dynamic features of banking crisis, in particular, volatility clustering and leverage effect, into the systemic risk measurement.

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