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Idiosyncratic Risks, Bailout, and Financial Crisis: A Copula Approach

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A B S T R A C T

The evidence on the dependence relationship of idiosyncratic risks among public-listed banks is unclear in the presence of the bailout event in the recent financial crisis. There is a suspicion about the effects of bailout regimes on the idiosyncratic risk circulated among different size-paired banks. We shed new light on the issue using a copula approach, an approach that allows for a possible skewed distribution and non-linear time series. We find that both stock return volatility and idiosyncratic risks increase significantly as stock returns increase after a bailout, especially in the money center group. We also find evidence suggesting that the dependence structure of idiosyncratic risks among size-paired banks decreases after bailout funding notably in Money Center-Large and Large-Small size-paired banks. The findings suggest that the expectation of using a Capital Purchase Program to reduce the probability of a contagion effect in this recent crisis is feasible and obtainable but with limited effects.

Keywords: Financial Crisis, Idiosyncratic Risks, Copulas

Ⅰ. Introduction

The evidence on the dependence structure of idiosyncratic risk among public-listed banks is unclear in the presence of a bailout event in the recent financial crisis. There is a suspicion about effects of bailout regimes on the idiosyncratic risk circulated among different size-paired banks. We address the issue using a copula approach, an approach that allows for a possible skewed distribution and non-linear time series. The main purpose of this paper is to assess the appropriateness and effects of the bailout program on the idiosyncratic risks of different sizes of banks during 2008-2009.

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To restore depositors' confidence and ease the liquidity crisis and possible contagion effect, Congress allocated $700 billion for the financial sector in the Emergency Economic Stabilization Act of 2008 (EESA). EESA authorized the U.S. Department of the Treasury to establish the Troubled Asset Relief Program (TARP) to bail out the financial industry. In July 2010, the financial regulation overhaul reduced TARP to $475 billion. Most of banks received their money through the Capital Purchase Program (CPP: health bank program), the largest one among 13 programs created under TARP. There were $204.9 billion (43.93 percent of TARP) of tax payers' money promised and actually invested into 707 banks during October 2008 through November 2009 as shown in Appendix A.

There are few empirical research studies focusing on bailout effects by the government acting as a lender of last resort on banks' idiosyncratic risks. How effective the government intervention is on banking industry

becomes an ongoing open question. Brei and Gadanecz (2012) assess the appropriateness and effects of government bailout programs in the G10 countries and four other developed countries (87 large internationally active banks) in pre-crisis (2000-2007) and during the crisis (2008-2010) periods. They compare new lending behavior (i.e. especially on syndicated loans) between bailout banks and non-bailout banks and find out that bailout banks involve more risky lending than non-bailout banks after receiving public funds. The findings suggest that government bailout programs do not discipline banks effectively from conducting risk-taking lending. Due to the limitation of data sources, the Brei and Gadanecz (2012) paper does not consider stock-related risks. Conventional wisdom suggests that the "too-big-to-fail" policy is the cause of larger banks introducing more risk-taking behavior than smaller banks. Black and Hazelwood (2012) measure the effect of TARP on bank risk-taking and find that the average risks of loan origination increase in large TARP banks but decrease in small TARP banks relatively to non-TARP banks. However, their sample consists of only 37 TARP banks and 44 non-TARP banks; therefore, it is very difficult to draw a general conclusion. Huerta et al., (2011) study the short-term impact of the TARP bailout on stock volatility and find that stock market volatility (i.e. a proxy for total risks of the firm) is significantly reduced upon the bailout funding. Different from my focus on CPP recipients and idiosyncratic risk, their paper emphasizes the market volatility change for four TARP recipient groups: banking, insurance, finance, and automotive industries. Duchin and Sosyura (2012) analyze the effect of government capital infusions on CPP banks and find that bailout improves the capitalization level of recipient banks but induces their risk-taking behavior in both lending and investing.

Veronesi and Zingales (2010) investigate the costs and benefits of the U.S. government intervention plan to the ten largest banks–Citigroup, Bank of America, JP Morgan Chase, Wells Fargo, Bank of NY Mellon, State Street Corp., Goldman Sachs, Morgan Stanley, Merrill Lynch—in the recent financial bailout and find that the value of banks' financial claims increases by $130 billion at the cost of tax payers for about $21 billion. They argue that if the government had applied the same terms Warren Buffett obtained from Goldman Sachs, then the taxpayers' gain would have increased from $39 to $55 billion.

Idiosyncratic risk is a non-systematic part of total risks, and it is a firm-specific risk and can be diversifiable. There is a gap in stock idiosyncratic risks for bailout banks in recent financial crisis. In this paper, there are three research questions to be answered. First, does size matter in idiosyncratic risks for CPP banks? Second, does the idiosyncratic risk shift in the presence of a bailout event? Third, does the dependence relationship in idiosyncratic risks change among different sizes of banks in the event of bailout?

The remainder of the paper is organized as follows. Section II reviews the extant literature. Section III describes the data and methodology, and provides descriptive statistics. Section IV presents the results, and Section V concludes the paper.

Ⅱ. Extant Literature

A. Size Effect

Prior studies find mixed results on how a bank's size is relevant to a financial crisis (Demsetz & Strahan 1997; Esqueda & Jackson 2011) Demsetz and Strahan (1995) find that bank size and risk are negatively correlated due to their diversification capacity and intense regulations. They find that the portfolio diversifications in large bank holding companies (BHCs) are more pronounced than those in smaller banks.

Esqueda and Jackson (2011) suggest that the implementation of the 1992 regulation on risk-based capital ratio can explain the reduction in a bank's risk. Banks are required to maintain a higher capital ratio if they have more risky lending (i.e. uncollateralized lending) and off-balance sheet activities. Mortgage lending is commonly classified as a safer activity by contrast. However, bank risk-taking theory suggests that federal deposit insurance corporation (FDIC) provides incentives for banks to take on higher risk projects which come along with moral hazard issues (Boyd & Gertler 1995). The implicit guarantee of a too-big-to-fail policy secures large banks from failure thus promoting more risk-taking activities among large banks. FDIC defends their position.

The recent crisis has provided strong arguments for opponents of the financial system. Interventions to avoid its collapse have severely undermined not only confidence in financial markets but also the market economy as a

whole. Once a financial institution has becomes so big or interconnected that its insolvency threatens the stability of the system, government must intervene.

B. Idiosyncratic Risks

Total risks of a firm consist of systematic risks and non-systematic risks. Stock return volatility (or variance) is a common proxy for total risk. Idiosyncratic risk (or volatility/variance) is a non-systematic part of total risk. Idiosyncratic risk reflects firm-specific information that is volatile in its nature. Modern portfolio theory suggests that investors should hold diversified portfolios to eliminate idiosyncratic risks; however, it is difficult to do so in reality (Barber & Odean 2000; Benartzi & Thaler 2001). As suggested by Merton (1987), investors are expected to have higher stock returns given higher idiosyncratic risks in the presence of incomplete information. In other words, under-diversified investors may demand a higher rate of return as compensation for bearing idiosyncratic risk. Many factors may contribute to the time-varying nature of firm-specific information such as the disclosure of high risk lending information, earnings announcements, or dividend payout news.

C. Why Does Idiosyncratic Risk Matter?

Conventional wisdom suggests that there is tradeoff between risks and returns. Goyal and Santa-Clara (2003) argue that systematic risks cannot account for the variance in total stock returns after controlling for the business cycling effect except the total risks which include systematic risks and idiosyncratic risks. Idiosyncratic risks especially contribute the most in driving the significance of average stock variance in explaining market returns. However, Bali et al. (2005) replicate the study and find no statistical significance when the value-weighted is substituted for the equally-weighted measure.

Stock returns mirror investors' confidence. During a time of financial crisis, bank runs can easily occur if the investors lose that confidence with the deposit institutions. The immediate capital injection from government funds is aimed at mitigating the possibility of the illiquidity risks to rebuild investors' or depositors' confidence without triggering the spillover effect. Therefore, idiosyncratic risk can play an important role as an indicator to quantify the magnitude of market reaction to such a bailout program.

D. Copula Function Approach in Financial Crisis

In this study, we examine whether there is a bailout effect in terms of the reduction in a possible contagion effect among size-paired banks. Financial contagion defined as the correlation between size-based banks. The traditional correlation method is essential to risk management. However, during extreme events, the correlation can be changed dramatically (Boyer *et al.* 1997). Traditional correlation method provides a simple and easy measure, but the observed significant increase or decrease in cross-market correlations around the events may not be necessary to produce contagion effects, but rather a bias due to the presence of heteroscedasticity, omitted variables, and endogeneity (Engle 2002; Forbes & Rigobon 2002; Sander & Kleimeier 2003; Claessens & Forbes 2004). The financial contagion is more likely to spread through trade linkages (i.e. interbank lending, common customer bases, and payment/settlement system) than through macroeconomic similarities, and the contagion tends to be regional rather than global (Claessens & Forbes 2004).

Researchers have provided several alternative methods for measuring time-varying conditional correlation. For example, the multivariate GARCH model (Engle 1982; Engle 2002; Forbes & Rigobon 2002; Chiang *et al.* 2007) and copula model (Costinot *et al.* 2000; Patton 2001; Cherubini *et al.* 2004; Rodriguez 2007; Boubaker & Jaghoubi 2011; Boubaker & Salma 2012). It is our intention to explore the process of the copula approach using time-series data in the setting of a financial crisis. More details about this approach will be discussed in the methodology section.

In Li's paper (2000), he uses the copula method to capture default correlation on credit default swap (CDS), which is believed to be one of major sources for the recent financial crisis. Li's model, also called the *Gaussian copula*, became popular this past decade in credit risk management due to its simplicity. However, it is criticized for not capturing extreme CDS default events in the recent subprime mortgage crisis. Donnelly and Embrechts (2010) argue that the *Gaussian* copula has its limitation since "the devil is in the tails." Gaussian copula is based on a normal distribution without taking into account the

occurrence of extreme events. The central in risk management is to manage the risks of an extreme event (Voinea & Anton 2009). However, extreme events are infrequent, and so data on them are scarce. There are some other copula models such as *Clayton* and *Gumbel* which are more appropriate for asymmetry tail distribution in the dependence test.

Ⅲ. Data and Methodology

A. Sample

There are total of 959 financial institutions receiving government funding under the Emergency Economic Stabilization Act (2008). This paper focuses on the banks that received funds through the Capital Purchase Program (CPP: Health bank program) during October 2008-November 2009. The 707 CPP recipients is the initial sample, which is collected from U.S. Department of the Treasury (2012), is cross-examined with the report from ProPublica (2015); *Wall Street Journal* (2015); CNN (2015); and Ericson, He, & Schoenfeld (2015) as shown in Appendix A.

The final sample is 167 public-listed CPP banks with 175,139 firm-daily observations that satisfied the following criteria:

(1) CPP banks are public-listed firms and traded on AMEX, NASDAQ or OTC.
(2) CPP banks have total assets data at the end of the second quarter in 2008 at FDIC.
(3) The daily stock returns and market capitalization of CPP banks are available at the Center for Research in Security Prices (CRSP).

This study clusters sample banks into four size groups in terms of total assets using the FDIC classification benchmark as the end of second quarter of 2008.

(1) Money centers: Total assets are greater than $ 10 billion.
(2) Large banks: Total assets are greater than or equal to $ 1 billion and less than $ 10 billion.
(3) Medium banks: Total assets are greater than or equal to $ 100 million and less than $ 1 billion.
(4) Small banks: Total assets are less than $ 100 million.

N is the number of firms in each subsample classified by total assets as 2008 Q2. Money Center: total assets greater than $10 bn; Large Banks: Total assets less than $10 bn and greater than $1bn; Medium Banks: total assets less than $1 bn and greater than $100 million; Small Banks: total assets less than $100 million; pre-bailout period (-250, -1) is one day and 250 days before the event date; event date (t=0) is the first CPP funding date for each bank. Post-bailout period (+1, +250) is one day and 250 days after the event date; market cap is market capitalization in thousand dollars; risk premium is the daily stock return minus the risk-free rate of return. Risk-free rate of return data is obtained from Professor Kenneth R. French data library (2015); Volatility is computed as standard deviation of daily stock returns using a 30-day rolling window method; mean difference t-test is Satterehwaite t test; median difference non-parameter test is Wilcoxon analysis. Symbols *, **, *** indicate the significance level of 10%, 5%, and 1%, respectively.

Two sample periods, pre-bailout and post-bailout, will be tested for the change and the dependence relation among different sizes of banks in which the first CPP funding date is the event dates (t=0). We collect stock daily returns and market capitalization for CPP banks from CRSP for the time period of 1,000 days before and after the event date respectively. We further compute stock return volatility for CPP banks given by stock return volatility as the standard deviation of CAPM model using 30-day rolling window.

Table 1 exhibits sample summary statistics using the CRSP data with only 250 trading days before (Panel A) and after (Panel B) the bailout date and calculates the changes in pre-bailout and post-bailout period (Panel C). The reason to use one year data is to focus on short-term impacts. Large banks and medium banks account for approximately 63 percent of the sample while money center and small banks stand for the rest. Market cap, an alternative proxy for firm size, aligns with the four size bank groups consistently which are classified using total assets data from FDIC. The market cap of CPP banks reduces one year after a bailout event economically and statistically significant across all sizes of banks as shown in Panel C of Table 1.

Daily returns of CPP banks recover after a bailout, notably the improvement in medium banks is significant at least 5 percent level when the Satterehwaite test in mean difference and Wilcoxon analysis in median difference are used respectively. Money center seems

Table 1. Sample Summary Statistics

Panel A Pre-Bailout (-250,-1)			Market Cap		Daily Return		Risk Premium		Volalility	
	N	Percent	mean	median	mean	median	mean	median	mean	median
Money Center	8	4.88%	$ 65,991,899 ***	$ 32,421,993	-0.0073	-0.0030	-0.0089 ***	-0.0115	0.0445 ***	0.0350
Large Banks	96	58.54%	$ 1,345,043 ***	$ 392,527	-0.0006 *	-0.0023	-0.0074 ***	-0.4433	0.0472 ***	0.0425
Medium Banks	56	34.15%	$ 229,648 ***	$ 48,399	-0.0009 *	0.0000	-0.0071 ***	-0.0080	0.0531 ***	0.0475
Small Banks	4	2.44%	$ 199,084 ***	$ 257,998	-0.0001	0.0000	-0.0070 ***	-0.0080	0.0403 ***	0.0346
Total	**164**	**100.00%**								
Panel B Post-Bailout (+1, +250)			**Market Cap**		**Daily Return**		**Risk Premium**		**Volalility**	
	N	Percent	mean	median	mean	median	mean	median	mean	median
Money Center	8	4.79%	$ 49,614,945 ***	$ 26,258,213	0.0019	-0.0008	0.0011	-0.0013	0.0605 ***	0.0502
Large Banks	97	58.08%	$ 887,090 ***	$ 279,676	0.0008	-0.0012	-0.0005	-0.0015	0.0527 ***	0.0486
Medium Banks	58	34.73%	$ 158,247 ***	$ 32,293	0.0013 **	0.0000	0.0009 *	0.0000	0.0573 ***	0.0529
Small Banks	4	2.40%	$ 133,621 ***	$ 67,807	0.0002	-0.0008	-0.0003	-0.0010	0.0456 ***	0.0421
Total	**167**	**100.00%**								
Panel C Changes in Pre-Post Bailout			**Market Cap**		**Daily Return**		**Risk Premium**		**Volalility**	
	N	Percent	mean	median	mean	median	mean	median	mean	median
Money Center	8	4.79%	$ (16,376,954) ***	$ (6,163,780) ***	0.0092	0.0022	0.0100 ***	0.0102 ***	0.0160 ***	0.0152 ***
Large Banks	97	58.08%	$ (457,953) ***	$ (112,851) ***	0.0014	0.0011 *	0.0069 ***	0.4418 ***	0.0055 ***	0.0061 ***
Medium Banks	58	34.73%	$ (71,401) ***	$ (16,106) ***	0.0022 **	0.0000 ***	0.0080 ***	0.0080 ***	0.0042 ***	0.0054 ***
Small Banks	4	2.40%	$ (65,463) ***	$ (190,191) ***	0.0003	-0.0008	0.0067 ***	0.0070 ***	0.0053 ***	0.0075 ***
Total	**167**	**100.00%**								

N is the number of firms in each subsample classified by total assets as 2008 Q2. Money Center: total assets greater than $10 bn; Large Banks: Total assets less than $10 bn and greater than $1bn; Medium Banks: total assets less than $1 bn and greater than $100 million; Small Banks: total assets less than $100 million; pre-bailout period (-250, -1) is one day and 250 days before the event date; event date (t=0) is the first CPP funding date for each bank. Post-bailout period (+1, +250) is one day and 250 days after the event date; market cap is market capitalization in thousand dollars; risk premium is the daily stock return minus the risk-free rate of return. Risk-free rate of return data is obtained from Professor Kenneth R. French data library (2015) Volatility is computed as standard deviation of daily stock returns using a 30-day rolling window method; mean difference t-test is Satterehwaite t test; median difference non-parameter test is Wilcoxon analysis. Symbols *, **, *** indicate the significance level of 10%, 5%, and 1%, respectively.

boosted the most among banks in terms of changes in daily returns with 0.0092 in mean after bailout. Similarly, risk premiums move upwardly across banks in the presence of a bailout program. Examining the volatility, we find that the volatility increase significantly at 1 percent level as stock returns rebound in the presence of bailout.

B. Idiosyncratic Risks (IR) Measures

Following the methodology of Bali et al. (2005) and Angelidis and Tressants (2009), the idiosyncratic risks are measured as the standard deviation of the regression residual from the CAPM market model using a 30-day rolling window method. Idiosyncratic risks are firm-specific and non-systematic risks, a part of the total risks (or volatility) after accounting for the systematic risks factor, and it is irrelevant because it can be eliminated by holding a well-diversified portfolio.

$$R_{it} - R_{ft} = \alpha_i + \beta_{it}(R_{mt} - R_{ft}) + \varepsilon_{it} \qquad (1)$$

To check whether idiosyncratic risks help explain the time-series variation, we further construct equally-weighted idiosyncratic risks (CAPM-EWIR) and value-weighted idiosyncratic risks (CAPM-VWIR) using market capitalization weighted based on Bail et al.,(2005).

CAPM beta may not sufficient to capture market systematic risks. Fama and French (1992; 1993) find size and book-to-market factors can improve the predictive power of the CAPM one-factor model. Based on the methodology of Fu (2009) and Ang et al. (2009), the idiosyncratic risks can be measured as the standard deviation of the regression residual from the Fama and French three-factor market model using a 30-day rolling window method (See French, 2015).

$$R_{it} - R_{ft} = \alpha_i + \beta_{it}(R_{mt} - R_{ft}) + s_{it}(SMB_t) + h_{it}(HML_t) + \varepsilon_{it} \qquad (2)$$

Where

R_{it} : Stock daily returns for firm *I* at time *t*

R_{ft} : Risk -free returns

$R_{it} - R_{ft}$: Excess returns or risk premium for firm *I* at time *t*

α_i : Intercept

ε_{it} : Regression residual

$\beta_{it}, s_{it}, h_{it}$: Risk factor sensitivity or loading for each risk factor

$(R_{mt} - R_{ft})$: Market risk premium at time t

(SMB_t) : The difference between the monthly return on a portfolio of small and large firms at time t

(HML_t) : The difference between the monthly return on a portfolio of high and low book-to-market stocks at time t

We compute idiosyncratic risk measurements using the CRSP data 250 trading days before and after the bailout date and calculate idiosyncratic risks' change in both pre- and post-bailout periods. Based on the FDIC size category, we group sample banks into four subgroups using total assets as a proxy for the size. The final sample should have stock returns and market capitalization data available at CRSP to construct CAPM idiosyncratic risks and Fama-French three-factor idiosyncratic risks. Details of variables appear in Appendix B.

Panel A of Table 2 exhibits idiosyncratic risks among bank groups using three measurements in the pre-bailout period (-250,-1) where the first CPP funding date for each specific bank is the event date (t=0). Similarly, idiosyncratic risks are measured in the post-bailout period (+1, +250) as in Panel B in order to compute the changes in the presence of bailout events. The changes in idiosyncratic risks from the pre-bailout to post-bailout period using CAPM-EWIR and FF-IR are positive and significant as shown in Panel C of Table 2. The findings provide evidence to the second research question and indicate that the idiosyncratic risks shift upwardly in the presence of CPP bailout funds. Note—some banks received CPP funding multiple times. We believe that the bailout effect occurred as soon as the first run of funding. This research intentionally ignores the subsequent funding effect.

CAPM-VWIR measure produces inconsistent results in Panel C than CAPM-EWIR and FF-IR across all sizes. Consequently, this measurement is excluded in the copula model test.

Table 2. Idiosyncratic Risk Statistics

Panel A Pre-Bailout (-250,-1)			**CAPM-EWIR**		**CAPM-VWIR**		**FF-IR**	
	N	Percent	mean	median	mean	median	mean	median
Money Center	8	4.88%	0.0242 ***	0.0185	0.1152 ***	0.1173	0.0081 ***	0.0054
Large Banks	96	58.54%	0.0412 ***	0.0386	0.0106 ***	0.0102	0.0008 ***	0.0000
Medium Banks	56	34.15%	0.0533 ***	0.0477	0.0184 ***	0.0276	0.0022 ***	0.0002
Small Banks	4	2.44%	0.0274 ***	0.0240	0.3199 ***	0.3153	0.0134 ***	0.0116
Total	**164**	**100.00%**						
Panel B Post-Bailout (+1, +250)			**CAPM-EWIR**		**CAPM-VWIR**		**FF-IR**	
	N	Percent	mean	median	mean	median	mean	median
Money Center	8	4.79%	0.0333 ***	0.0293	0.1057 ***	0.1069	0.0108 ***	0.0072
Large Banks	97	58.08%	0.0464 ***	0.0461	0.0105 ***	0.0103	0.0011 ***	0.0000
Medium Banks	58	34.73%	0.0579 ***	0.0538	0.0178 ***	0.0259	0.0027 ***	0.0047
Small Banks	4	2.40%	0.0297 ***	0.0268	0.3173 ***	0.3143	0.0139 ***	0.0124
Total	**167**	**100.00%**						
Panel C Changes in Pre-Post Bailout			**CAPM-EWIR**		**CAPM-VWIR**		**FF-IR**	
	N	Percent	mean	median	mean	median	mean	median
Money Center	8	4.79%	0.0091 ***	0.0108 ***	-0.0095 ***	-0.0104 ***	0.0027 ***	0.0018 ***
Large Banks	97	58.08%	0.0052 ***	0.0075 ***	-0.0001 **	0.0001	0.0003 ***	0.0000 **
Medium Banks	58	34.73%	0.0046 ***	0.0061 ***	-0.0006 ***	-0.0017 ***	0.0005 ***	0.0045 **
Small Banks	4	2.40%	0.0023 ***	0.0028 **	-0.0026 ***	-0.0010 ***	0.0005 ***	0.0008 **
Total	**167**	**100.00%**						

N is the number of firms in each subsample classified by total assets as 2008 Q2. Money Center: total assets greater than $10bn; Large Banks: Total assets less than $10 bn, and greater than $1bn; Medium Banks: total assets less than $1 bn, and greater than $100 million; Small Banks: total assets less than $100 million; pre-bailout period (-250, -1) is one day and 250 days before the event date; Event date (t=0) is the first CPP funding date for each bank. The post-bailout period (+1, +250) is one day and 250 days after the event date; Idiosyncratic Risk is computed as standard deviation of regression residual from CAMP or Fama-French 3-factor models using a 30-day rolling window method; CAPM-EWIR is equally-weighted idiosyncratic risk based on the CAPM model; CAPM-VWIR is thevalue-weighted idiosyncratic risk based on CAPM using market capitalization; FF-IR is idiosyncratic risk based on the Fama-French three-factor model. The mean difference t-test is Satterehwaite t test; the median difference non-parameter test is Wilcoxon analysis. Symbols*, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

C. Methodology

1. Normality test

Normality tests are frequently a basic assumption for most statistical methods with the null hypothesis that the random variable is to be normal distributed. The evidence in Table 3 exhibits the results of Kolmogorov-Smirnov tests for normality in each data series for the period of one year (250 trading days) before and after the bailout event. The fat tails or positive kurtoses in the distribution of each series indicate the likelihood of joint extreme events. The normality tests for the distributions of idiosyncratic risks reject the null hypothesis of a non-normal distribution of the data regardless of the bank size, idiosyncratic measures, and a bailout event. The skewness of idiosyncratic risks may create a spurious association when no relation exists. The results indicate that a copula approach is a necessary way to examine the data.

2. White Noise Test –Portmanteau (Q) test

In most econometric models, the variance of the disturbance term is assumed to be constant (homoscedasticity). It is a white noise test for serial independence applied to the estimated standardized residuals. The data is transformed by taking a logarithm and first-difference before this autocorrelation test. Results in last column in Table 3 indicate that our data reject the null hypothesis of no autocorrelation effect at the 1 percent level for both CAPM equally-weighted and Fama and French three-factor idiosyncratic risks measures.

3. ARMA-GARCH Model

Czado et al (2012) show that ARMA -GARCH models are sufficient to remove the time dependence in the sample. To remove serial correlation and standardize the return residuals, the time series data in this paper is filtered using the ARMA-GARCH model. The ARMA process is just the combination of an AR and a MA process. The autoregressive process, or AR, is a stochastic difference equation in which the current value of a series is linearly related to its past values plus an additive stochastic shock.

Following the methodology of Weiβ (2012), we fit the ARMA(p_1, q_1)-GARCH(p_2, q_2) model to each of our idiosyncratic risks measures in each size data to account for time-varying volatility. After filtering the data, we further transform the true observation into pseudo-observation using empirical distribution function.

4. Copula Model

Nelson (2006) provides a detailed introduction about the copula model. A copula is multivariate distribution function whose marginal distributions are uniform. The basic properties for copula are grounded, two-increasing, and non-negative volume of a rectangle. Copula is grounded for every point u_1 and u_2 in I^2.

Table 3. Normality Test of Idiosyncratic Risks

		CAPM-EWIR				CAPM-VWIR			FF-IR			
Panel A Pre-Bailout (-250, -1)	N	Skewness	Kurtosis	K-S test	Q (20)	Skewness	Kurtosis	K-S test	Skewness	Kurtosis	K-S test	Q (20)
Money Center	1717	1.4284	1.0410	0.1873 ***	621.1068 ***	-0.5184	-0.8684	0.1495 ***	1.4487	1.3831	0.1715 ***	303.8619 ***
Large Banks	23429	0.6911	-0.1645	0.1069 ***	152.5267 ***	0.2439	-0.7163	0.0839 ***	3.3661	15.0073	0.3720 ***	229.0879 ***
Medium Banks	13385	1.4704	2.7129	0.1327 ***	122.4918 ***	-0.1452	-1.9560	0.3010 ***	3.1152	13.2241	0.2820 ***	201.1907 ***
Small Banks	721	1.0126	0.5955	0.1422 ***	488.9308 ***	0.2266	-1.6942	0.1901 ***	1.48663	2.5018	0.1509 ***	261.2865 ***
		CAPM-EWIR				**CAPM-VWIR**			**FF-IR**			
Panel A Post-Bailout (+1, +250)	N	Skewness	Kurtosis	K-S test	Q (20)	Skewness	Kurtosis	K-S test	Skewness	Kurtosis	K-S test	
Money Center	1724	1.3336	2.4199	0.1115 ***	594.1617 ***	-0.4207	-0.9087	0.0877 ***	2.0908	5.3010	0.1912 ***	230.4490 ***
Large Banks	23694	0.9414	1.7921	0.0606 ***	136.3436 ***	0.1441	-0.6667	0.0305 ***	5.0584	34.1154	0.3540 ***	187.6904 ***
Medium Banks	13943	5.0074	41.3835	0.1354 ***	172.0678 ***	-0.0651	-1.9477	0.2630 ***	8.8848	99.4771	0.3670 ***	168.3444 ***
Small Banks	728	0.8245	-0.1443	0.1140 ***	432.3058 ***	0.5035	-1.3259	0.1572 ***	0.8588	0.0408	0.1308 ***	219.3267 ***

N is the number of firm-daily observations in each subsample classified by total assets as 2008 Q2. Money Center: total assets greater than $10bn; Large Banks: Total assets less than $10 bn, and greater than $1bn; Medium Banks: total assets less than $1 bn, and greater than $100 million; Small Banks: total assets less than $100 million; pre-Bailout period (-250, -1) is one day and 250 days before the event date; event date (t=0) is the first CPP funding date for each bank. Post-bailout period (+1, +250) is one day and 250 days after the event date; Idiosyncratic Risk is computed as residual of CAMP or Fama-French 3-factor models using 30-day rolling window method; CAPM-EWIR is equally-weighted idiosyncratic risk based on CAPM model; CAPM-VWIR is value-weighted idiosyncratic risk based on CAPM using market capitalization; FF-IR is idiosyncratic risk based on Fama-French three-factor model. K-S test is the Kolmogorov-Smirnov test for Normality; Q (20) is the statistics of Portmanteau (Q) test for autocorrelation of 20 lags after taking logarithm and first-difference. Symbols*, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

5. Copula Estimation

Assume that$(\varepsilon_1, \varepsilon_2)$ has multivariate distribution function F and continuous univariate marginal distribution functions F_1 and F_2. In order to investigate the dependence, we fit copula-based models:

$$\hat{F}_n = F(\varepsilon_1, \varepsilon_2; \theta) = C(F_1(\varepsilon_1), F_2(\varepsilon_2); \theta) \quad (3)$$

where, C is a copula function that exists uniquely by Sklar's Theorem (Sklar, 1959) parameterized by the vector $\theta \in R$. The corresponding model density is the product of the copula density c and the marginal densities f_1 and f_2:

$$f(\varepsilon_1, \varepsilon_2; \theta) = c(F_1(\varepsilon_1), F_2(\varepsilon_2); \theta) f_1(\varepsilon_2) f_2(\varepsilon_2) \quad (4)$$

where, c is the copula density of model (3) and is given by:

$$c(u_1, u_2; \theta) = \frac{\partial^2 C(u_1, u_2; \theta)}{\partial u_1 \partial u_2}, \ (u_1, u_2 \epsilon [0, 1]^2) \quad (5)$$

The copula families we consider are Clayton, Gumbel, Frank, Plackett, Normal (Gaussian), and Student-t (Nelsen, 2006). Appendix C describes copula families' distribution functions and their parameter space as well as their tail-dependence formulas. Clayton and Gumbel are the copula models with asymmetric tails, thus we need to estimate the tail dependence using the coefficients of lower and upper tail dependence respectively.

The copula parameters for each of copula families are estimated by two steps. First, estimating the parameters of the marginal distributions separately by EDF function:

$$\hat{F}_t(x) = \frac{1}{T+1} \sum_{(t=1)}^{T} I\{\hat{\varepsilon}_{i,t} \leq x\} \quad (6)$$

Second is estimating the parameters of a parametric copula by solving the following problem:

$$\theta = \mathrm{argmax}_{\theta} \sum_{(t=1)}^{T} ln\, c(\hat{u}_t, \hat{v}_t; \theta) \quad (7)$$

where, θ are the copula parameters. $\hat{u}_t$ and $\hat{v}_t$ are pseudo observations calculated from equation (6).

6. Goodness of fit (Gof) tests

Graphical tools provide a useful starting point for possible copula families to describe observed dependence. However, an independence test should be verified in particular if the strength of dependence appears to be rather small. Following the suggestion of Genest and Favre (2007) , we proceed with a simple bivariate independence test based on Kendall's tau (τ) process as the best copula model change after bailout.

An approximate p-value for the test statistic can be performed using a parametric bootstrap or a fast-large sample testing procedure based on multiplier central limit theorem (MCLT) (Kojadinovic & Yan 2010). Bootstrapping is time-consuming in computation, and its results are similar and consistent with those in MCLT: We use MCLT for six copula families in this paper.

7. Akaike's Information Criteria (AIC)

It is difficult to compare the better fitting model when the two or more models fail to reject the null hypothesis in the Gof test. As suggested by Frees and Valdez (1998), Breymann et al. (2003), and Rodriguez (2007), Akaike's Information Criteria (AIC) is suitable to adjust for the small sample bias. We compute AIC for each fitting model given by

$$\text{AIC} = -2 \log L(\theta) + 2k + \frac{2k(k+1)}{n-k-1} \quad (8)$$

where log L (θ) is the maximized log likelihood function, and k is the number of parameters estimated, and n is the sample size. According to this criterion, the best fitting model is the one with the lowest AIC.

A summary of the complete copula-based methodological framework is given as below:

Step 1: Estimating the filtered returns from ARMA(p_1, q_1)-GARCH(p_2, q_2) model

Step 2: Using empirical distribution function to transform $\hat{\varepsilon}_t$ into pseudo observations

Step 3: Applying copula models for each dataset

Step 4: Identifying the optimal configuration of the

copula model in each data using copula-Gof metrics and AIC

Step 5: Computing the lower/upper tail dependence coefficient for each copula model.

There are several advantages to using copula. First, it can detect non-linear dependence. Second, it is able to measure dependence for heavy tail distribution. Third, it is very flexible in estimation methods regardless of parametric, semi-parametric or non-parametric estimations. Fourth, the computation is faster and stable with a two-stage estimation.

Ⅳ. Results

A. Idiosyncratic Risks and Size

Panel A and B of Table 4 display an inverse relationship between bank size and idiosyncratic risks at the 1 percent significance level. Both CAPM equally-weighted and Fama and French three-factor measurements decrease significantly as market cap increases in the pre-bailout period (-250,-1) and post-bailout period (+1, +250). Market cap is the proxy for firm size, and the first CPP funding date for each specific bank is the event date (t=0). These results provide an answer to the first research question that the size does matter in idiosyncratic risk regardless of bailout events or measurements. The findings add supporting evidence to the existing idiosyncratic risks literature especially in the bailout event during a financial crisis.

Consistent with previous literature, daily stock returns are positively and significantly related to idiosyncratic risks, which indicates that higher returns are associated with higher firm-specific risks (Goyal & Santa-Clara 2003). In addition, volatility positively relates to idiosyncratic risks regardless of CAPM or Fama-French three-factor models.

B. Correlation of Idiosyncratic Risks among Size Pairs

Table 5 examines the correlation relationship of idiosyncratic risks among different size pairs using raw data. Panel A and B exhibit CAPM equally-weighted idiosyncratic risks and the Fama-French three-factor model respectively. Six size pairs include MC-L (money center—large banks), MC-M (money centers—medium banks), MC-S (money center—small banks), L-M (large banks—medium banks), L-S (large banks—small banks), M-S (medium banks—small banks). The Pearson r correlation is linear correlation. The Spearman rho (ρ) rank-order correlation is a nonparametric measure of association based on the ranks of the data values. Kendall's tau (τ) is a nonparametric measure of association based on the number of concordances and discordances in paired observations. The range of all three correlation measures

Table 4. Correlation Tests

Panel A Pre-Bailout (-250, -1)	Market Cap	Daily Return	Volatility	CAPM-EWIR	FF-IR
Market Cap	1	0.009	-0.071	-0.113	-0.098
		0.1651	<.0001	<.0001	<.0001
Daily Return	0.009	1	0.007	0.023	0.004
	0.1651		0.2650	0.0004	0.5164
Volatility	-0.071	0.007	1	0.828	0.136
	<.0001	0.2650		<.0001	<.0001
CAPM-EWIR	-0.113	0.023	0.828	1	0.142
	<.0001	0.0004	<.0001		<.0001
FF-IR	-0.098	0.004	0.136	0.142	1
	<.0001	0.5164	<.0001	<.0001	
Panel B Post-Bailout (+1, +250)	**Market Cap**	**Daily Return**	**Volatility**	**CAPM-EWIR**	**FF-IR**
Market Cap	1	0.013	-0.051	-0.095	-0.061
		0.0500	<.0001	<.0001	<.0001
Daily Return	0.013	1	0.009	0.049	0.019
	0.0500		0.1590	<.0001	0.0040
Volatility	-0.051	0.009	1	0.660	0.329
	<.0001	0.1590		<.0001	<.0001
CAPM-EWIR	-0.095	0.049	0.660	1	0.315
	<.0001	<.0001	<.0001		<.0001
FF-IR	-0.061	0.019	0.329	0.315	1
	<.0001	0.0035	<.0001	<.0001	

are within -1 and +1.

In Panel A of Table 5, three correlation measures produce very consistent results. The pair wise correlation coefficients are positive in both pre-bailout and post-bailout periods, which consist of 1,000 days before and after the CPP funding date. It is important to note that the correlation of idiosyncratic risks is reduced across all pairs as shown in the last column where Kendall tau is the indicator, indicating that the probability that contagion in the banking industry is reduced in the presence of a bailout program.

Table 5. Correlation Measures and Idiosyncratic Risks

Panel A	Panel A.1 Pre-Bailout			Panel A.2 Post-Bailout			Changes in Kendall τ
	Linear Correlation	Rank Correlation		Linear Correla	Rank Correlation		
Pairs	Pearson r	Spearman ρ	Kendall τ	Pearson r	Spearman ρ	Kendall τ	
MC-L	0.7980 ***	0.6593 ***	0.4744 ***	0.5843 ***	0.5569 ***	0.3918 ***	-0.4744
MC-M	0.7725 ***	0.7019 ***	0.5120 ***	0.4477 ***	0.4639 ***	0.3184 ***	-0.1936
MC-S	0.6853 ***	0.4785 ***	0.3256 ***	0.5745 ***	0.4222 ***	0.2894 ***	-0.0362
L-M	0.8913 ***	0.8011 ***	0.6137 ***	0.4454 ***	0.5815 ***	0.4164 ***	-0.1973
L-S	0.7831 ***	0.6197 ***	0.4406 ***	0.4669 ***	0.4267 ***	0.2936 ***	-0.1470
M-S	0.7532 ***	0.5790 ***	0.4074 ***	0.3542 ***	0.3618 ***	0.2468 ***	-0.1606
Panel B	Panel B.1 Pre-Bailout			Panel B.2 Post-Bailout			Changes in Kendall τ
	Linear Correlation	Rank Correlation		Linear Correlation	Rank Correlation		
Pairs	Pearson r	Spearman ρ	Kendall τ	Pearson r	Spearman ρ	Kendall τ	
MC-L	0.3168 ***	0.2767 ***	0.1881 ***	-0.0058	0.0490	0.0327	-0.1554
MC-M	0.3013 ***	0.2467 ***	0.1646 ***	0.0384	-0.0467	-0.0317	-0.1963
MC-S	0.2819 ***	0.2798 ***	0.1902 ***	0.3379 ***	0.3417 ***	0.2302 ***	0.0400
L-M	0.3709 ***	0.1905 ***	0.1281 ***	-0.0119	0.0188	0.0126	-0.1155
L-S	0.3330 ***	0.2453 ***	0.1655 ***	0.0328	0.0334	0.0221	-0.1434
M-S	0.2857 ***	0.1986 ***	0.1337 ***	-0.0219	-0.1040 ***	-0.0693 ***	-0.2030

Table 6. ARMA-GARCH Results

Panel A	Panel A.1 Pre-Bailout Period				Panel A.2 Post-Bailout Period			
Autoregressive Models	Money Center	Large Banks	Medium Banks	Small Banks	Money Center	Large Banks	Medium Banks	Small Banks
p_1	5	2	2	7	3	1	3	2
q_1	4	2	2	3	4	1	1	2
Constant, μ	0.007	0.001	0.001*	-0.001	-0.002*	-0.004***	-0.004***	-0.000
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
AR(1), φ_1	0.612***	0.999***	0.114	0.978***	0.629***	0.357***	0.666***	1.102***
	(0.077)	(0.179)	(0.132)	(0.074)	(0.065)	(0.035)	(0.024)	(0.055)
MA(1), θ	-0.053	-1.570***	-0.380***	-0.495***	-0.082	-0.912***	-0.953***	-0.633***
	(0.070)	(0.182)	(0.125)	(0.071)	(0.059)	(0.015)	(0.012)	(0.049)
Garch models								
p_2	5	2	2	6	5	1	1	6
q_2	3	1	1	3	1	1	1	1
Constant, α_0	0.002	0.019	0.006	0.005***	0.002	0.013*	0.064**	0.008
	(0.002)	(0.016)	(0.005)	(0.001)	(0.002)	(0.007)	(0.029)	(0.014)
L1.Arch, α_1	0.193***	0.059	0.116***	0.116**	0.028	0.089*	-0.013	0.099**
	(0.059)	(0.037)	(0.039)	(0.053)	(0.038)	(0.050)	(0.010)	(0.048)
L1. Garch, β	-1.010***	-0.150	0.601*	0.570***	0.642**	0.636***	-0.540	0.014
	(0.086)	(0.931)	(0.334)	(0.178)	(0.248)	(0.167)	(0.670)	(1.665)
Log-likelihood	924.272	587.547	555.781	1197.918	894.96	202.964	265.342	902.372
Degree of freedom	10.055	9.735	30.184	11.457	20.322	3.811	3.574	4.060
Q(20)	21.175	26.595	18.359	7.510	17.433	26.227	23.720	2.031
p-value	0.387	0.147	0.564	0.378	0.625	0.158	0.255	0.845

Table 6. ARMA-GARCH Results (continued)

Panel B	Panel B.1 Pre-Bailout Period				Panel B.2 Post-Bailout Period			
Autoregressive Models	Money Center	Large Banks	Medium Banks	Small Banks	Money Center	Large Banks	Medium Banks	Small Banks
p1	5	1	1	2	3	3	1	3
q1	5	1	1	2	3	3	1	3
Constant, μ	0.002*	0.009***	0.012***	0.001	-0.001	0.000	0.003**	0.000
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)
AR(1), φ1	0.716***	0.136***	0.106***	1.155***	0.728	-0.112	0.227***	1.535***
	(0.237)	(0.026)	(0.027)	(0.062)	(0.479)	(0.132)	(0.033)	(0.273)
MA(1), θ	-0.330	-0.973***	-0.959***	-0.866***	-0.308	-0.672***	-0.981***	-1.165***
	(0.235)	(0.006)	(0.008)	(0.061)	(0.481)	(0.132)	(0.007)	(0.274)
Garch models								
p2	5	2	1	4	5	4	1	2
q2	4	1	1	2	2	1	1	1
Constant, α0	0.056***	3.017	2.916***	0.230***	0.061	0.460*	1.657**	0.941
	(0.016)	(2.963)	(0.475)	(2.475)	(0.024)	(0.303)	(0.683)	(0.586)
L1.Arch, α1	0.419***	0.019	0.013	21.635	0.314	0.204***	0.063	0.992
	(0.106)	(0.031)	(0.018)	(232.94)	(0.090)	(0.075)	(0.056)	(0.619)
L1. Garch, β	-0.031	-0.644	-0.895***	0.826*	-0.448**	0.602**	-0.177	-0.767***
	(0.113)	(1.592)	(0.204)	(0.375)	(0.186)	(0.284)	(0.448)	(0.159)
Log-likelihood	133.230	1537.684	1516.525	724.897	71.065	1359.900	1423.417	679.707
Degree of freedom	3.540	3.010	3.540	2.020	3.388	5.325	4.972	2.000
Q(20)	31.089	22.399	6.330	57.210	29.259	26.872	14.720	8.550
p-value	0.154	0.319	0.998	0.378	0.183	0.138	0.792	0.287

This table reports the maximum likelihood estimates and standard errors (in parentheses) for the parameters of the marginal distribution model. Panel A, Idiosyncratic risks, is computed as standard deviation of the residual of CAPM models using a 30-day rolling window method. Panel B, Idiosyncratic risk, is computed as standard deviation of the residual of the Fama-French three-factor models using a 30-day rolling window method. There are four data series based on bank size: (1) Money center (2) Large banks (3) Medium banks (4) Small banks. Pre-bailout/post-bailout periods are the time period of 1,000 days before/after CPP funding date. Q (20) is the statistics of Portmanteau (Q) test for autocorrelation of 20 lags after data filtering using ARMA-GARCH models. Symbols *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

In the case of idiosyncratic risks measured by the Fama-French three-factor, the results are quantitatively similar as shown in Panel B except for the MC-S pair. All three correlation measurements exhibit positive but near zero changes in the event of a bailout for money center-small pair. Overall, correlation coefficients show reductions or even become statistically insignificant as shown in Panel B. This implies that there is a reduction in the dependent structure between size-based pairs after a government bailout. The plausible explanation is that the Fama and French three-factor measure has taken into account the size effect.

C. Autocorrelation Tests and ARMA-GARCH Models

Table 6 reports the results from ARMA (p_1, q_1) and GARCH (p_2, q_2) processes using the maximum likelihood estimates and standard errors for the parameters of the marginal distribution model of four size groups. The purpose of these processes is to ensure an autocorrelation-free time series for copula tests. White noise test-Portmanteau (Q) statistics confirm that the filtered datasets are free of the autocorrelation effect in the standardized residuals computed with 20 lags. Idiosyncratic risk is computed as a standard deviation of the residual of the CAPM model and Fama-French three-factor models using a 30-day rolling window method in Panel A and Panel B respectively. Both panels include data from 1,000 trading days in pre-bailout and post-bailout period.

D. Copula Results

In previous traditional correlation analysis, we provided evidence about the reduced dependent relationship among size-paired banks in the event of bailout. We now explore the change of dependence using the copula approach. Table

7 reports the summary of copula parameters and goodness of fit tests 1,000 days before bailout (Panel A) and 1,000 days after bailout (Panel B) using CAPM equally-weighted idiosyncratic risks. Kendall's tau is empirically produced with pseudo-observations which are transformed from real observations using an empirical distribution function. In a goodness of fit test, we use a CvM statistic (*p*-value) estimate based on MCLT to identify possible copula families to model the data. To adjust for a possible small sample bias, the final model for each size pair is selected based on the lowest AIC.

Results from Table 7 show that half of the best-fitted copula models change after bailout except MC-L, L-S, and M-S pairs. Plackett copula and Gaussian copula are the best-fit models for MC-L and L-S pairs each individually. The dependence using copula parameters in both size pairs is decreased, which provides consistent results as shown in the correlation tests. However, the M-S pair exhibits reverse results when the Clayton copula is the best fitted model for the pair. In addition, the lower tail dependence decreases after the bailout. If an increase in tail dependence is a dimension of the contagion phenomenon (Forbes & Rigobon 2002), then a decrease in tail dependence indicates the reduced possibility of a contagion effect.

To evaluate the dependence structure change for the other three size pairs in the case of the best fit copula model changing over time, we need to use standardized measurement, Kendall's tau. Kendall's tau shown in Table 7 is empirical estimates using the data filtered by ARMA-GARCH process and transformed by an empirical distribution process. Among the three size pairs, the dependence relationship between MC-M and MC-S exhibits an increased tendency but insignificant statistically and economically. Similarly, the change in dependence for the L-M pair is reduced but insignificantly. Copula tests with the Fama-French three-factor provide quantitatively similar results and can be provided upon request. It is reasonable to believe that the idiosyncratic risks measure from the Fama and French three-factor model does not reveal statistically significant dependent relationships for size-paired groups since the size factor is accounted for in the asset pricing model. The findings in the copula model confirm the decreased dependence between MC-L and L-S bank groups at the event of government bailout program.

Table 7. Copula Parameters and Goodness of Fit Tests

Pairs	Best Fit Copula model	no of observations	Kendall's τ	changes in dependence in Kendall's τ	Copula Parameter	changes in dependence in Copula parameter	Gof Cvm test (p-value)	Standard errors	LF	AIC	λu	λL
Panel A Pre-Bailout												
MC-L	Plackett	1000	0.0538**		**1.272**		0.673	0.120	3.300	-4.596		
MC-M	Gumbel	1000	0.0145		1.015		0.309	0.019	1.603	-1.202	0	0.020
MC-S	Gaussian	1000	-0.0357*		-0.056		0.151	0.033	1.679	-1.354		
L-M	Clayton	1000	-0.0037		-0.007		0.055	0.031	0.041	1.922		
L-S	Gaussian	1000	-0.0042		**-0.008**		**0.035**	0.030	0.074	1.856		
M-S	Clayton	1000	-0.0205		**-0.038**		0.179	0.031	4.001	-5.998	0.020	0
Panel B Post-Bailout												
MC-L	Plackett	925	-0.0408*		**0.833**	decrease	**0.037**	0.083	1.666	-1.328		
MC-M	Plackett	925	0.0367*	increase	1.178		0.452	0.116	1.479	-0.954		
MC-S	Frank	925	-0.0127	increase insignificantly	-0.114		0.167	0.199	0.192	1.620		
L-M	Gaussian	925	-0.0052	decrease insignificantly	-0.008		0.187	0.032	7.807	-13.610		
L-S	Gaussian	925	-0.0084		**-0.013**	decrease	0.638	0.036	0.197	1.610		
M-S	Clayton	925	0.0276		**0.057**	increase	0.476	0.039	1.586	-1.168	0.000	0

Idiosyncratic riskis computed as standard deviation of residual of CAPM models using a 30-day rolling window method. There are six pairs of bank groups: (1) MC-L is money center-large banks pair (2) MC-M is money center-medium banks pair (3) MC-S is money center-small banks pair (4) L-M is large banks-medium banks pairs (5) L-S is large banks-small banks pair (6) M-S is medium banks-small banks pair; Pre-bailout/ post-bailout periods are the time period of 1,000 days before/after CPP funding date; Gof CvM test (p-value) is estimated based on multiplier central limit theorem.; LF is the maximized log likelihood value; AIC is Akaike information criteria. The appropriate copula model is chosen to model the dependence of idiosyncratic risk between size-based pairs. Symbols*, **, *** indicate the significance level of 10%, 5%, 1%, respectively.

Table 8. Multiple Breakpoints Test for Idiosyncratic Risk Series

Break Test	F-statistic	Critical Value
l vs. *l+1*		
0 vs. 1 *	67.079	11.470
1 vs. 2	6.323	12.950

Note: This table provides tests for multiple breaks in idiosyncratic risk series. This sequential testing of *l* versus *l+1* breaks using the methods outlined by Bai and Perron (1998) and Bai and Perron (2003). * indicate the test is statistically significant at 5% level of significance based on the critical values provided by Bai and Perron (2003).

E. Robustness Test

One might doubt that whether the results of this research still hold when a bailout date is determined endogenously. To answer this question, we first use the Bai-Perron multiple breakpoint test (Bai & Perron, 1998; Bai & Perron, 2003) to detect a break date for the idiosyncratic risk series. The results of the Bai-Perron multiple breakpoint test are reported in Table 8. Second, we re-apply the copula methodology to the data with a new break date and then compare its results with those of Table 7.

According to Table 8, one breakpoint exists in the idiosyncratic risk series. In detail, we reject the nulls of a 0 breakpoint in favor of the alternatives of 1 breakpoint as the F-statistic shows 67.079 and greater than the critical value of 11.470. In the second line of the table, the test of 1 versus 2 breakpoints does not reject the null as the F-statistic shows 6.323 and smaller than the critical value of 12.950. After the new break date (bailout date) is determined, we cross-check with the real bailout date; and to no surprise, the endogenously determined bailout date is only three days after the real bailout date. This implies that bailout actions do have an impact on banks' idiosyncratic risk; and more importantly, the change in idiosyncratic risk happens quickly after bailout intervention (only 3 days). In a table available upon request, we replicate Table 7 with a new break date, and the results remain the same. This is reasonable since both the real bailout date and newly-determined bailout date are only three days different.

Ⅴ. Discussion and Conclusions

This paper examines the changes of the dependence structure in idiosyncratic risks among different size-paired bank groups at the presence of a government bailout program in the recent financial crisis. We provide copula models as an alternative method to evaluate the possible reduction of contagion effect after the bailout when the time-series data are skewed and in a non-linear distribution.

The findings provide evidence to the first and second research questions which indicate that the idiosyncratic risks shift upwardly in the presence of CPP bailout funds using the CAPM equally-weighted model and the Fama-French three-factor models. The results are more pronounced for the money center than other smaller sizes of banks. The results from increases of investors' risk premium and stock return volatility support the argument that investors are expected to be compensated with higher returns at given increased risks. Larger banks are rich in human capital and resources to reduce firm-specification risks by diversification; however, investors seem unconfident with the bank's performance when the transparency and regulations for banks' derivative activities are not fully disclosed or implemented.

Using traditional linear correlation and rank-based correlation methods, we can confirm the reduced possibility of a contagion effect after the bailout. The copula method provides additional evidence suggesting that dependent relationship of idiosyncratic risks among size-paired banks decreases after a bailout funding, especially MC-L and L-S pairs. The findings suggest that the expectation of using a CPP program to reduce the probability of a contagion effect in this recent crisis is accomplished but is limited to certain pairs of groups. As the literature suggested, a copula model is an appropriate model to detect possible contagion effect or co-movement when the distribution is not normal or linear. However, the correlation in the idiosyncratic risks using the Fama & French three-factor model between size-paired groups exhibits a decreasing dependent relationship after receiving CPP funding. The coefficients of correlation estimates are relatively small at about the 0.3 or below level. Using the copula method with the Fama and French three-factor idiosyncratic risk measurement provides a limited

contribution.

The findings in this paper are very important to policy makers to assess the appropriateness and functions of bailout programs. CPP funds provide immediate capital injections to financial distressed banks to improve the liquidity and prevent possible bank runs; at the same time, they control possible contagion effects well. This paper contributes new insight on exploring the copula approach to identify possible co-movement in idiosyncratic risks among bailout banks in the recent financial crisis. In addition, the possible changes of the best-fitted copula family in the presence of an extreme event and bailout program demand attention from future research.

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Appendix A. Emergency Economic Stabilization Act (2008)

Program	Promised (in Billion)	Percent	Actually invested (in Billion)	Number of Recipients	Memo
Preferred Stock Investment (Unlimited)	187.500		187.500	2	Fannie Mae and Freddie Mac Bailout
TARP					
Capital Purchase Program	**204.900**	**43.926%**	**204.900**	**707**	**The 'Healthy Bank' Program**
Automotive Industry Financing Program	81.300	17.429%	79.300	4	Loan to the auto industry
Systemically Significant Failing Institutions	69.800	14.964%	67.800	1	Money for AIG
Targeted Investment Program	40.000	8.575%	40.000	2	More money for BofA and Citigroup
Making Home Affordable	29.900	6.410%	3.600	125	The mortgage loan modification plan
Public-Private Investment Program	21.900	4.695%	18.400	9	Public-Private Toxic Asset Purchases
FHA Refinance Program	8.100	1.736%	0.050	1	Refinancing underwater mortgage
Housing Finance Agency Innovation Fund	7.600	1.629%	1.100	19	Money for states hit hardest by crisis
Term Asset-Backed Securities Loan Facility	1.400	0.300%	0.000	0	Fed program to spur lending
Community Development Capital Initiative	0.783	0.168%	0.570	84	Cheap loans for community develop banks
Auto Supplier Support Program	0.413	0.089%	0.413	2	Financing for Auto parts suppliers
Small Business and Community Lending Initiati	0.368	0.079%	0.368	1	Program to ease small biz credit market
Asset Guarantee Program	0.000	0.000%	0.000	2	Limiting losses for Citi and BofA
Subtotal Total	466.464	100.000%	416.501	959	
Grand Total	653.964		604.001		

Source: Troubled Asset Relief Progress (TARP) Monthly Report to Congress-February 2013. Retrieved from http://www.treasury.gov/initiatives/financialstability/reports/Documents/February%202013%20Monthly%20Report%20to%20Congress.pdf

Appendix B. Variable Definitions

Variables	Description/Measurement	Data Source
Idiosyncratic Risks	It is firm-specific risks or non-systematic risks	CRSP
CAPM-EWIR	EWIR is the equally-weighted average idiosyncratic risks. It is measured as standard deviation of daily stock returns residual in CAPM models using a 30-day rolling window method.	CRSP and Kenneth R. French Data Library
CAPM-VWIR	VWIR is the value-weighted idiosyncratic risks using market capitalization weights. It is measured as residual of daily stock returns in CAPM models using a 30-day rolling window method.	CRSP and Kenneth R. French Data Library
FF-IR	FF-IR is Fama and French idiosyncratic risks. It is measured as standard deviation of daily stock returns residual in Fama-French 3-factor models using a 30-day rolling window method.	CRSP and Kenneth R. French Data Library
Bank Groups	Classified sample banks into 4-size groups based on the total assets as 2008 Q2	FDIC
Money Center	Total assets are greater than $10bn	FDIC
Large Banks	Total assets are less than $10 bn, and greater than $1bn	FDIC
Medium Banks	Total assets are less than $1 bn, and greater than $100 million	FDIC
Small Banks	Total assets are less than $100 million	FDIC
Market Cap	Market capitalization	CRSP
Daily Return	Daily stock return	CRSP
Risk Premium	It is firm-specific risks premium. We subtract risk-free rate from daily stock return, while Risk-free rate is one-month T-bill rate	CRSP and Kenneth French Data Library
Volatility	It is stock return volatility and is measured as standard deviation of daily stock returns in regression models using a 30-day rolling window method	CRSP

Appendix C. Copulas Distribution and Parameter

Copula Family	Copula Distribution Cθ (u.v)	Parameter Range	Tail dependence λL	Tail dependence λU
Gaussian	$\varphi_\rho\left(\varphi^{-1}(\mu_x), \varphi^{-1}(\mu_y)\right)$	-1 < ρ < 1		
Student's t	$T_{\vartheta,\rho^N}\left(t_\vartheta^{-1}(u), t_\vartheta^{-1}(v)\right)$	-1 < ρ < 1	$2t_{\vartheta+1}\left(-\frac{\sqrt{\vartheta+1}\sqrt{1-\rho^T}}{\sqrt{1+\rho^T}}\right)$	$2t_{\vartheta+1}\left(-\frac{\sqrt{\vartheta+1}\sqrt{1-\rho^T}}{\sqrt{1+\rho^T}}\right)$
Clayton	$\left[\max\left(u^{-\theta}+v^{-\theta}-1,0\right)\right]^{-1/\theta}$	θ ∈ [-1, ∞)\ {0}	$2^{-1/\theta}$	0
Frank	$-\frac{1}{\theta}\ln\left(1+\frac{(e^{-\theta u}-1)(e^{-\theta v}-1)}{e^{-\theta}-1}\right)$	θ ∈ (-∞, ∞) \ {0}	0	0
Gumbel	$\exp\left(-\left[(-\ln u)^\theta+(-\ln v)^\theta\right]^{1/\theta}\right)$	θ ∈ [1, ∞)	0	$2-2^{1/\theta}$
Plackett	$C(u,v)=\frac{\left[1+(\theta-1)(u+v)\right]\pm\sqrt{\left[1+(\theta-1)(u+v)\right]^2-4uv\theta(\theta-1)}}{2(\theta-1)}.$	θ ∈ [1, ∞]		

Source: Nelsen (2006) , Boubaker and Salma (2011), and Rodriguez (2007)
λ_L is the coefficient of lower tail dependence. λ_U is the coefficient of upper tail dependence. ϑ are the degree of freedom.