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Do Systemic Risk measures predict the Uncertainty Shocks?

Master Thesis in Financial Economics

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Preface

This paper represents the research study of Jialin Zheng, Master Financial Economics student at the Erasmus University Rotterdam. This master thesis is written in order to complete the graduation phase of the Master Financial Economics.

The subject of this thesis is about how the new measures of systemic risk after financial crisis of 2007-2009 predict the uncertainty shocks at the micro, macro and higher-order level.

I would like to thank everyone that helped me writing this thesis. A special word of thanks is for my supervisor, Dr. Melissa Lin for her valuable comments and recommendations.

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Jialin Zheng

Abstract

The financial crisis of 2007-2009 prompted a profusion of newly proposed measures of systemic risk. The academic literatures however haven't related the systemic risk with the uncertainty shocks. This paper try to study how these measures of systemic risk predict the uncertainty shocks at the micro, macro and high-order level through the Granger-causality in quantiles.

Keywords: systemic risk, uncertainty shocks, Granger-causality, quantile regression

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1. Introduction

As shown in many studies that the financial system crisis is an important force to drive the macroeconomic downturns, there are more and more new ways to measure the systemic risks.

But are they really good at predicting the financial crisis? How to test this problem? According to Bloom (2009) and Bloom, Floetotto, Jaimovivh, Sapora-Eksten and Terry (2012), uncertainty shocks have significant relations with financial crises. Many literatures have studied the transmission mechanism on how the uncertainty shocks affecting the economy. Christiano, Motto, and Rostagno(2014) shows that the uncertainty shocks are the important driving force for the business cycle through constructing standard monetary dynamic general equilibrium model. Bachmann and Bayer (2012) find that uncertainty shocks and economic activities is more like “wait and see” while the uncertainty shocks are more persistent and have larger effects on economic activities in the US. Basu and Bundick (2012) show the feature of economy’s response to uncertainty shocks.

However the market has many dimensions, as a measurement of the market health, uncertainty shocks also are multidimensional. This paper concerns about the uncertainty shocks effects on economy from a more comprehensive prospect.

From the uncertainty shocks aspect, there are three levels used in this paper: micro, macro and high order level. According to Nicholas, Anna and Laura (2016), they divide the uncertainty shocks into three levels: micro, macro and high order level. They show that these uncertainty shocks have a strong countercyclical property through investigating the relations among micro, macro and high-order levels uncertainty shocks with GDP growth.

From the market aspect, there are four dimensions 19 measures in total used in this paper to measure the market situation. It covers volatility, co-movement, specific risks and liquidity and credit. The measures mainly come from the literatures over the past twenty years. The detail will be provided in methodology part.

Giglio, Stefano, Kelly, Bryan, and Pruitt, Seth (2016) have studied the relations between macroeconomic and 19 systemic risk measures and find these measures have significant predictive information for the lower tail of macroeconomic. They mainly focus on the new systemic measures effects on macroeconomic under lower bound but what happened to uncertainty shocks on micro, macro and high order level under a higher bound? That is do systemic risk measures predict the uncertainty shocks?

To answer this question, this paper mainly uses granger causality on quantile regression model to do the test and the data focus on US market. The main finding in this paper is that the measures of volatility can captures more information about uncertainty shocks on micro level while the institution specific risks can captures more information about high order level uncertainty shocks and most of measures show negative relations with high order level uncertainty shocks which may mean that the exacerbation of crisis will narrow the disagreements among firms. However macro uncertainty shocks are more complicated and varied, individual measures cannot predict the macro level uncertainty shocks very well. This paper investigates the relations between the systemic risk measures with the uncertainty shocks from second moment and may provide more evidence and more rich information for these new measures effects.

The paper is arranged as follows. Section 1 and 2 are about introduction and discuss related literatures about the systemic risk and uncertainty shocks. The methodology used in this paper will be introduced in section 3. Section 4 discusses the empirical study on these new systemic measures and uncertainty shocks. Lastly the results and conclusion will be presented tin section 5.

2. Literature Review

Having been suffering from the financial crisis in recent years, more and more papers focus on understanding the financial cycle through investigating uncertainty shocks.

Bloom (2009) and Bloom, Floetotto, Jaimovivh, Sapora-Eksten and Terry (2012) both indicate that uncertainty shocks have significant relations with financial crises. Bachmann and Bayer (2012) constructs business-level uncertainty shocks in Germany and the US and show that in Germany, the relationship of uncertainty shocks and economic activities is more like “wait and see” while in the US, the uncertainty shocks are more persistent and have larger effects on economic activities. Christiano, Motto, and Rostagno(2014) use US data through a standard monetary dynamic general equilibrium model to show that the uncertainty shocks are the important driving force for the business cycle. Basu and Bundick (2012) shows the feature of economy’s response to uncertainty shocks. Nicholas, Anna and Laura(2016) show that uncertainty shocks show a strong countercyclical property through investigating the relations among micro, macro and high-order levels uncertainty shocks with

GDP growth. Gilchrist, Sim and Zakrajsek (2013) study the transmission mechanism on how the shocks affecting the economy. Giglio, Stefano, Kelly, Bryan, and Pruitt, Seth (2016) evaluates the relations between macroeconomic shocks and 19 systemic risk measures and construct a systemic risk indexes which proved to have significant predictive information for the lower tail of macroeconomic.

Having been proved that uncertainty shocks have significant effects for the business countercyclical, this paper try to find how the new systemic risk measures based on recent papers predict the uncertainty shocks from micro, macro and high-order levels through granger causality on quantile regression. The main purpose is to investigate these new systemic risk measures effects on uncertainty shocks from different dimensions. This may provide more rich information about the formation of financial risks.

3. Methodology

Since this paper studies the relationship between the new measures of systemic risk and the uncertainty shocks, the methodology begins with defining the measures of the systemic risk and the measures of uncertainty shocks.

3.1 Measures of systemic risk

The systemic risk measures used in this paper are based on Stefano Giglio, Bryan T. Kelly, Seth Pruitt (2015). There are 4 parts including 19 new systemic risk measures which cover the volatility, co-movement, specific risks, liquidity and credit. The data is mainly about the 20 largest financial institutions in US except that the data of size concentration is from the largest 100 institutions. The brief introductions of these measures are as below:

3.1.1 Volatility

- Real volatility is constructed by computing the within-month standard deviation of daily returns.
- Turbulence is based on Kritzman and Li (2010). It is defined as follow:

$$\text{Turbulence} = (r_t - \mu)'\Sigma^{-1}(r_t - \mu)$$

where r_t is the vector of financial institutions' return, μ and Σ are the historical mean and variance-covariance matrix. This measure computes excess volatility comparing to the realized squared returns of financial institutions with their historical volatility.

- CatFin indicates the time-varying VaR of financial institutions at 99% confidence level. Allen, Bali and Tang (2012) construct it by fitting the cross-sectional distribution of financial institution returns for the bottom 10% tail in each period, and then define the 1% of returns on the fitted distribution in each period as the CatFin.

- Aggregate book leverage and market leverage indicate the potential instability and shock when large financial institutions are highly levered.

- Size concentration (Herfindal index) is defined as follow:

$$\text{Herfindal}_t = N \frac{\sum_{i=1}^{N} ME_i^2}{\left(\sum_{i=1}^{N} ME_i\right)^2}$$

- This index captures the potential instability under the threat default of the largest firms.

3.1.2 Co-movement

- Absorption ratio, based on Kritzman and Li (2010), captures the fraction of N financial institutions' return variance explained by the first K<N principal components:

$$\text{Absorption (K)} = \frac{\sum_{i=1}^{K} \text{VaR}(PC_i)}{\sum_{i=1}^{N} \text{VaR}(PC_i)}$$

Δ Absorption ratio is defined as the difference between long and short estimation windows:

$$\Delta\text{Absorption (K)} = \text{Absorption (K)}_{\text{short}} - \text{Absorption (K)}_{\text{long}}$$

- Dynamic Causality Index (DCI) captures the Granger-causality relationships among all N(N-1) pairs of N financial institutions returns. If P-value$\leq$0.05, then the granger-causality relation is significant. Billio, M., A.Lo, M. Getmansky and L.Pelizzon(2012) construct this index to indicate the interconnections between the financial institutions. The index is defined as follow:

$$\text{DCI} = \frac{\sum_{i=1}^{N} \sum_{j \neq i} (j \rightarrow i)}{N(N-1)}$$

- Internatioanal Spillover Index is based on Diebold and Yilmaz (2009). It is obtained from Economic Research Forum website. This index captures the total extent of spillover across the series considered.

3.1.3 Specific risks

- CoVaR and ΔCoVaR,

According to Adrian and Brunnermeier (2011), CoVaR is defined as the value of risk (VaR) of the financial system under the condition that institution i is in distress. Denote event $C\left(X^i\right)$ of institution i, where X^i from the definition of VaR_q^i (q-quantile of institution i's value at risk):

$$P\left(X^i \leq VaR_q^i\right) = q$$

Then denote CoVaR as q-quantile of the conditional probability distribution:

$$P\left(X^{system} \leq CoVaR_q^{system\,|\,C(X^i)} \middle| C(X^i)\right) = q$$

where $CoVaR_q^{system\,|\,C(X^i)}$ means the q-quantile of financial system VaR on the condition of event $C\left(X^i\right)$

ΔCoVaR which captures the marginal contribution of institution i to whole financial system is defined as follow:

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system\,|\,X^i=VaR_q^i} - CoVaR_q^{system\,|\,X^i=VaR_{0.5}^i}$$

- Financial firm's marginal expected shortfall (MES and MES-BE) indicates the expected shortfall of a firm when the whole system is in bad days

MES measure is based on Acharya, Pedersen, Philippon and Richardson (2010). MES is defined as the average net equity returns of each firm i on the condition of the 5% worst market outcomes:

$$MES_{5\%}^i = E\left[R^i | R^{system} \leq q_{0.5}\right]$$

where $q_{0.5}$ is the worst 5% outcome of the financial system return.

MES-BE measure is based on Brownlees and Engle (2011). MES-BE is defined as follow:

$$\text{MES-BE}_{i,t-1} = \sigma_{i,t}\rho_t E_{t-1}\left(\epsilon_{m,t}\middle|\epsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho_t^2}E_{t-1}\left(\epsilon_{i,t}\middle|\epsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right)$$

where $(\epsilon_{m,t}, \epsilon_{i,t})$ are the shocks of market return and firm return respectively and C denotes the conditioning systemic event. $(\sigma_{i,t}, \sigma_{m,t})$ is defined from GARCH model. The time varying correlations ρ_t defined from DCC approach.

3.1.4 Liquidity and credit

- AIM is an illiquidity measure from Amihud's (2002). It is defined as follow:

$$\text{AIM}_t^i = \frac{1}{K}\sum_{\tau=t-K}^{t}\frac{|r_{i,\tau}|}{\text{turnover}_{i,\tau}}$$

  It captures weighted average illiquidity on stock-level.

- Ted spread equals to 3-month LIBOR minus 3-month T-bill rate.
- Default spread equals to BAA bond yield minus AAA bond yield
- GZ is a credit measure from Gilchrist and Zakrajsek (2012). Firstly, it constructs the individual credit spreads by computing the difference between individual unsecured corporate bonds' yield and the yield of synthetic treasury bond with the same cash flows. Then the index can be obtained by averaging the individual credit spreads across all maturities and firms.
- Term spread is the slope of treasury yield curve and obtained from Global Financial Data.

The statistics of all the systemic risk measures data are summarized in Table1.

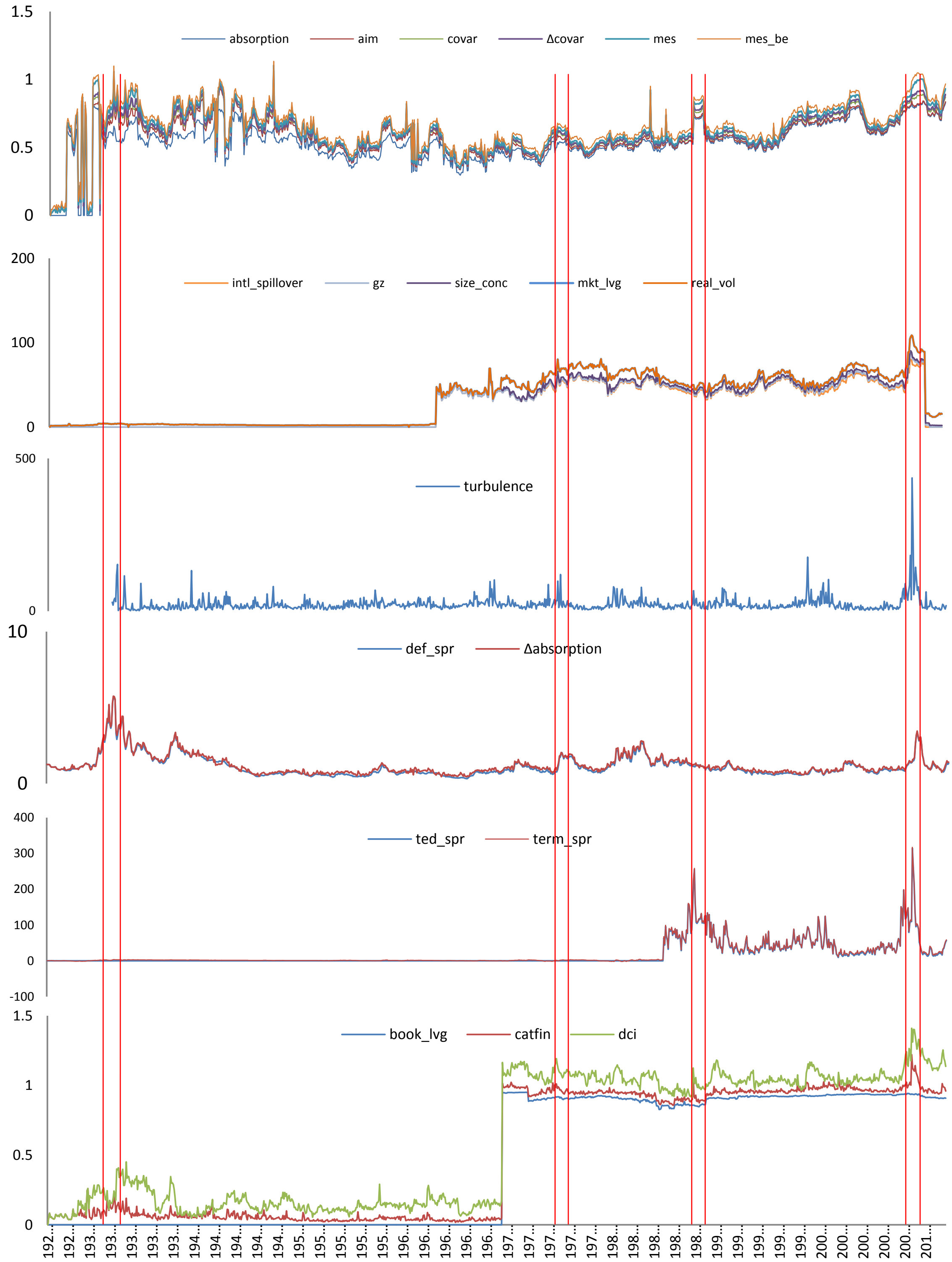
Table1: Statics of systemic measures

Variable	Obs	Mean	Std. Dev.	Min	Max
absorption	999	0.5560	0.1127	0.2962	0.8361
aim	1,031	0.0410	0.0411	0.0041	0.3827
covar	999	0.0200	0.0103	0.0060	0.0626
Δ covar	999	0.0078	0.0050	0.0015	0.0318
mes	1,004	0.0222	0.0151	0.0047	0.0983
mes_be	1,031	0.0304	0.0064	0.0154	0.0665
book_lvg	510	0.9127	0.0256	0.8275	0.9505
catfin	1,031	0.0507	0.0290	0.0161	0.2826
dci	994	0.1047	0.0555	0.0026	0.3079
def_spr	1,032	1.1388	0.7083	0.3200	5.6400
Δ absorption	999	0.1009	0.0837	−0.2351	0.3901
intl_spill~r	565	47.8671	9.2467	30.4000	80.3000
gz	452	1.5892	1.0368	0.5235	7.9078
size_conc	1,027	2.4497	0.5884	1.4795	4.5240
mkt_lvg	509	8.3538	3.6598	3.1968	25.3126
real_vol	1,031	0.0188	0.0104	0.0081	0.1499
ted_spr	325	55.8089	42.7099	9.5240	314.2970
term_spr	1,032	1.4702	1.1405	−1.9100	4.3900
turbulence	957	22.7140	24.8999	1.5526	435.8874

Note: The start dates of these variables respectively are (form the top to bottom): 1927, 1926, 1927, 1927, 1927, 1926, 1969, 1926, 1928, 1926, 1927, 1963, 1973, 1926, 1969, 1926, 1984, 1926 and 1932.

Figure 1 contains main 6 trends of these systemic measures. These systemic measures have a very similar tendency. During the big financial crisis after 1926, for examples (between two red lines in figure 1): great depression from 1929 to 1930, oil crisis from 1973 to 1974, Black Monday on 1987 and financial crisis in 2008, all the measures show an upward tendency. However these measures are very volatile, many spikes of them still arise when no crisis happens. According to Stefano Giglio, Bryan T. Kelly, Seth Pruitt (2015), there are three potential reasons: the influences of noisy in these systemic risk measures; Although these measures reflect the stress of the crisis, after the regulatory from government or other institutions or the self-correction of the market, the formation of crisis is interrupted; the formation of crisis will happen only if the systemic risk measures increase at the same time.

Figure1: The trends of systemic risk measures.



Note: Each pair of red lines indicates a period of financial crisis.

Table2: The correlations among the systemic risk measures

	absorption	aim	covar	delta_covar	mes	mes_be	book_lvg	catfin	dci	def_spr	delta_absorption	intl_spillover	gz	size_conc	mkt_lvg	real_vol	ted_spr	term_spr	turbulence
absorption	1.00																		
aim	-0.03	1.00																	
covar	0.64	0.09	1.00																
delta_covar	0.69	0.00	0.97	1.00															
mes	0.66	0.08	0.94	0.95	1.00														
mes_be	0.35	-0.17	0.27	0.34	0.41	1.00													
book_lvg	0.24	-0.06	0.13	0.10	0.10	-0.06	1.00												
catfin	0.39	0.24	0.51	0.45	0.50	0.24	0.11	1.00											
dci	0.12	-0.09	0.30	0.32	0.38	0.25	0.08	0.23	1.00										
def_spr	0.30	0.17	0.62	0.54	0.55	0.25	-0.25	0.45	0.28	1.00									
delta_abso˜n	-0.50	-0.05	-0.28	-0.28	-0.29	-0.17	-0.05	0.12	-0.03	-0.12	1.00								
intl_spill˜r	0.42	-0.13	0.40	0.45	0.45	0.25	0.12	0.19	0.17	0.34	-0.15	1.00							
gz	0.73	-0.12	0.75	0.71	0.71	0.36	0.33	0.62	0.26	0.37	-0.23	0.31	1.00						
size_conc	0.01	0.24	0.19	0.07	0.13	-0.21	0.40	0.17	0.07	0.16	-0.08	-0.07	0.45	1.00					
mkt_lvg	-0.14	0.11	0.22	0.19	0.17	-0.09	0.30	0.24	0.51	0.46	0.13	0.29	0.14	0.01	1.00				
real_vol	0.44	0.11	0.66	0.60	0.63	0.35	0.13	0.86	0.27	0.52	0.05	0.19	0.69	0.17	0.19	1.00			
ted_spr	0.10	0.05	0.19	0.20	0.20	0.34	-0.34	0.48	0.12	0.38	0.02	-0.16	0.24	-0.20	0.09	0.49	1.00		
term_spr	0.32	0.00	0.33	0.36	0.38	0.33	-0.22	0.16	0.17	0.43	-0.17	0.31	0.16	-0.05	-0.08	0.19	-0.07	1.00	
turbulence	0.13	-0.08	0.19	0.18	0.18	0.20	0.10	0.46	0.12	0.13	0.03	0.06	0.41	-0.01	0.17	0.54	0.54	-0.08	1.00

Table 2 shows the correlations among these systemic risk measures. Here I use the moving average of next 2 months to substitute the missing data in order to calculate the correlations. Most of the correlations are small except that two group variables: CoVaR & Δ CoVaR & MES and CatFin & Real Volatility, because these measures have high relativity. Some of the correlations are negative which indicates that these systemic risk measures predict the crisis from different angles.

3.2 Measures of uncertainty shocks

The measures of uncertainty shocks are classified by 3 types: micro level, macro level and high-order level.

3.2.1 Micro Uncertainty

The micro uncertainty is measured by cross-sectional interquartile range (IQR) of firm-level sales growth. The firm-level sales data is obtained from Wharton Research Data Services (WRDS) between 1962Q1 and 2011Q4 based on the firms who have at least 100 quarters. There are 2498 firms in this sample. The micro uncertainty is computed as follow:

$$\mathrm{MIU_t} = \mathrm{IQR}\left(\frac{\mathrm{S_{i,t+4}} - \mathrm{S_{i,t}}}{\frac{1}{2}(\mathrm{S_{i,t+4}} + \mathrm{S_{i,t}})}\right)$$

Where $\mathrm{MIU_t}$ is the micro uncertainty in quarter t. $\mathrm{S_{i,t}}$ is the sales of firm i in quarter t. Next using Hodrick-Prescott filter to have detrend $\mathrm{MIU_t}$ and calculate the percentage deviations. The result is showed in Figure 2.

3.2.2 High order Uncertainty

The sample obtained from the Survey of Professional Forecasters: Measures of Cross-Sectional Dispersion for Quarterly Forecasts for REAL GDP (RGDP) from 1968Q4 to 2011Q4.

Firstly, because the sample gives the 25^{th} and 75^{th} percentile of the forecasts for Q/Q growth, I calculate the forecast GDP growth as the mean of them:

$$\mathrm{E(GDP_{t+1})} = \frac{1}{2}(\mathrm{GDP_{t+1,25}} + \mathrm{GDP_{t+1,75}})$$

Where $\mathrm{GDP_{t+1,25}}$ and $\mathrm{GDP_{t+1,75}}$ are the 25^{th} and 75^{th} percentile of the forecasts for Q/Q growth.

Then the high order uncertainty is computed as the cross-sectional standard deviation of the forecasts:

$$\mathrm{HU_t} = \sqrt{\frac{1}{2}\left[\mathrm{GDP_{t+1,25}} - \mathrm{E(GDP_{t+1})}\right]^2 + \left[\mathrm{GDP_{t+1,75}} - \mathrm{E(GDP_{t+1})}\right]^2}$$

The micro uncertainty is based on four quarter growth rate. In order to make the high order uncertainty comparable to the micro uncertainty, the $\mathrm{HU_t}$ is adjusted as below:

$$\widehat{\mathrm{HU}}_\mathrm{t} = \frac{\sum_{i=0}^{3} \mathrm{HU_{t+i}}}{4}$$

Lastly, detrend the high order uncertainty through the same method as used for the micro uncertainty and calculate the percentage deviations. The result is showed in Figure 2.

3.2.3 Macro uncertainty

The sample data comes from CBOE VXO index and S&P 500 index. Because the data of CBOE VXO index only starts from 1986 so the monthly standard-deviation of the daily S&P500 index is used before 1986. The CBOE VXO index implied volatility based on the S&P100 (OEX) options. The data process used here is based on Bloom (2009).

The macro uncertainty is computed as follow:

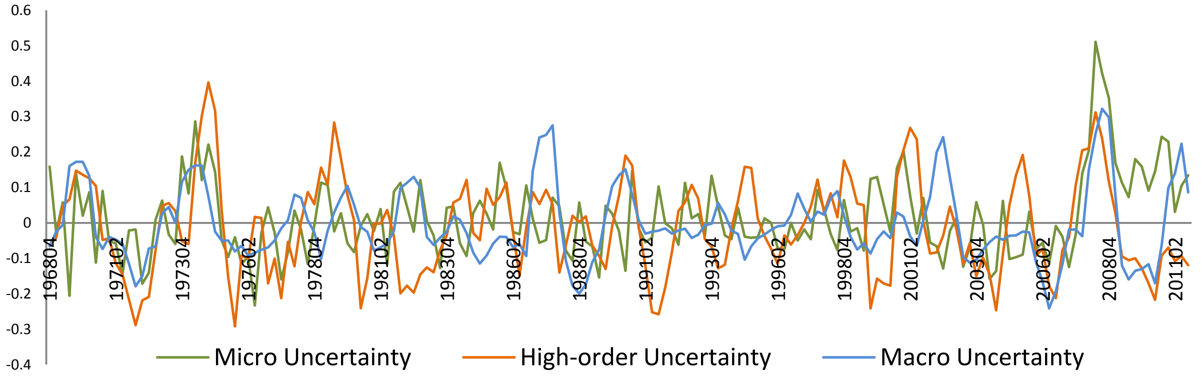
$$\mathrm{MAU_t} = \frac{1}{\mathrm{N}} \sum \mathrm{MAU_{t,i}}$$

Where $\mathrm{MAU_{t,i}}$ is the set of data in quarter t. Then adjust the macro uncertainty as below:

$$\widehat{\mathrm{MAU}}_\mathrm{t} = \frac{\sum_{i=0}^{3} \mathrm{MAU_{t+i}}}{4}$$

This series covers 1968Q4-2011Q4. Then calculate the percentage deviation from the HP trend. The result is presented in Figure 2.

Figure 2: Percentage deviation of uncertainty



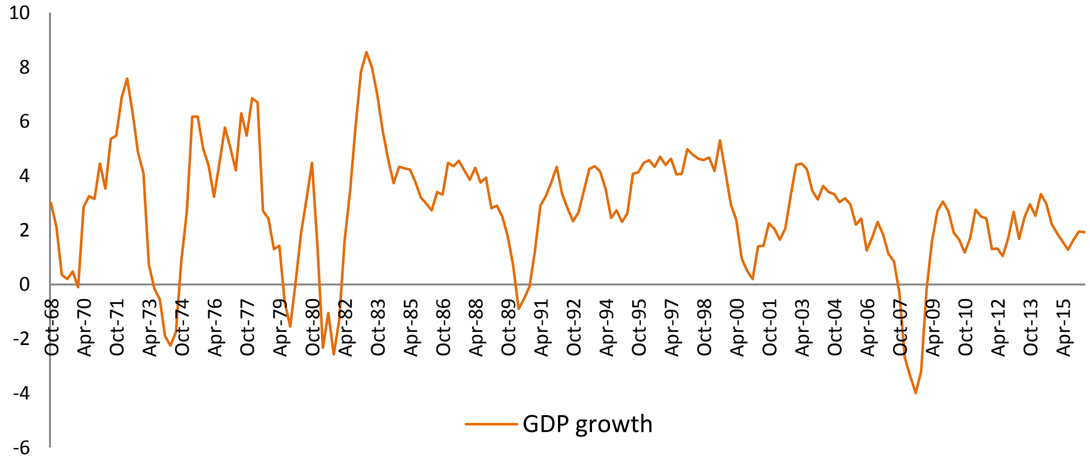
3.2.4 GDP growth

The GDP growth data in quarter t are calculated as:

$$\widehat{\mathrm{GDP}_t} = \frac{\sum_{i=0}^{3} \mathrm{GDP}_{t+i}}{4}$$

Where GDP_{t+i} is the real GDP's percent change from preceding period, quarterly, seasonally adjusted annual rate in quarter t+i. The data obtained from BEA from 1968Q4 to 2011Q4.

Figure3: GDP growth



3.3 The relationships among macro, high-order and micro uncertainty shocks

Having regressing each of them on the other one, we can see the relationship between them. The results are showed in table 3, table 4 and table 5. The statistics and correlations among them are shown in table 6.The main conclusions are: (1) all the three uncertainties are positive with each other statistically; (2) all types of uncertainty are negative with GDP growth which means they are countercyclical statistically.

Table3: The relationship between micro uncertainty and high-order uncertainty.

micro	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
highorderuncertainty	.0692118	.0630069	1.10	0.274	-.0551648	.1935884
gdpg	-.0209559	.0034504	-6.07	0.000	-.0277669	-.0141448
_cons	.0737391	.0122205	6.03	0.000	.0496157	.0978625

Regress micro uncertainty on high-order uncertainty.

Table 4: The relationship between macro uncertainty and high-order uncertainty.

highorderu~y	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
macro	.2206225	.094069	2.35	0.020	.0349287	.4063163
gdpg	-.0144878	.0042009	-3.45	0.001	-.0227805	-.0061951
_cons	.0341958	.0148339	2.31	0.022	.0049134	.0634782

Regress high-order uncertainty on macro uncertainty.

Table 5: The relationship between macro uncertainty and micro uncertainty.

macro	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
micro	.1756546	.0734263	2.39	0.018	.0307098	.3205993
gdpg	-.0126947	.0035273	-3.60	0.000	-.0196576	-.0057317
_cons	.0298324	.0127517	2.34	0.020	.0046603	.0550045

Regress macro uncertainty on micro uncertainty.

Table 6: The statistics and correlations among uncertainty measures

Variable	Obs	Mean	Std. Dev.	Min	Max
gdpg	173	2.8499	2.2987	-4.0000	8.5500
micro	173	0.0135	0.1104	-0.2333	0.5110
higho	173	-0.0139	0.1336	-0.2921	0.3962
macro	173	-0.0040	0.1027	-0.2415	0.3217

	micro	gdpg	higho	macro
micro	1			
gdpg	-0.46238	1		
higho	0.27773	-0.43637	1	
macro	0.320389	-0.37163	0.360857	1

3.4 Granger Causality in Quantilies

Following Chia-Chang Chuang , Chung-Ming Kuan , Hsin-yi Lin (2007), Granger-Causality in quantile can be defined as follow:

$$Q_{y_t}(\tau|I_{t-1}{}^{x,y}) = Q_{y_t}(\tau|I_{t-1}{}^{y}), \quad \tau \in (0,1) \tag{1}$$

where $Q_{y_t}(\tau|\cdot)$ is the conditional distribution in $\tau-\mathrm{th}$ quantile of y_t . ${I_{t-1}}^{x,y}$ is the information set of x and y up to time t-1. ${I_{t-1}}^{y}$ is the information set of y up to time t-1.

Writing $y_{t-1}=\left[y_{t-1},\cdots,y_{t-p}\right]'$, $x_{t-1}=\left[x_{t-1},\cdots,x_{t-q}\right]'$, and $z_{t-1}=\left[1,\ \ y'_{t-1,p},\ \ x'_{t-1,q}\right]'$, the $\tau-\mathrm{th}$ conditional quantile of y_t cen be defined as follow:

$$Q_{y_t}(\tau|z_{t-1})=a(\tau)+y'_{t-1,p}\alpha(\tau)+x'_{t-1,q}\beta(\tau)=z'_{t-1}\theta(\tau) \qquad (2)$$

The estimation of $\theta(\tau)$ equals to minimizing asymmetrically weighted absolute deviation:

$$\min\sum_{t=1}^{T}\rho_\tau[y_t-z'_{t-1}\theta(\tau)] \qquad (3)$$

where $\rho_\tau(u)=u[\tau-I(u<0)]$. According to Koenker, Bassett (1978), $I(u<0)$ is a characteristic function that when $u<1$, the function equal to 1 otherwise equal to 0. Problem in (4) can be solved by linear programming algorithm.

Given that linear model of conditional quantiles (2), testing (1) is to test:

$$H_0\colon \beta_T(\tau)=0,\quad \tau\in(0,1)\quad T\in(1,q) \qquad (4)$$

Rejecting this hypothesis suggests that: $\beta(\tau)\neq 0$, so x Granger causes y otherwise x is Granger non-causality for y.

Define $\hat{\theta}(\tau)$ as the solution of (1), according to Koenker (2005), the convergence in distribution of $\hat{\theta}(\tau)$ under large sample is:

$$\sqrt{T}\left[\hat{\theta}(\tau)-\theta(\tau)\right]\xrightarrow{D}\sqrt{\tau(1-\tau)}\,\sqrt{\Omega(\tau)}\,N(0,I_k) \qquad (5)$$

where $\Omega(\tau)=D\tau^{-1}M_{zz}D\tau^{-1}$, $D(\tau)=\lim_{T\to\infty}\frac{\sum_{t=1}^{T}f_t[F_t^{-1}(\tau)]z_{t-1}z'_{t-1}}{T}$,

$M_{zz}=\lim_{T\to\infty}\frac{\sum_{t=1}^{T}z_{t-1}z'_{t-1}}{T}$. F_{t-1} and f_t are the conditional distribution functions and density of y_t.

Writing $R\theta(\tau)=\beta(\tau)$, then

$$\sqrt{T}\left[\beta_T(\tau)-\beta(\tau)\right]=\sqrt{T}R\left[\hat{\theta}_T(\tau)-\theta(\tau)\right]\xrightarrow{D}\sqrt{\tau(1-\tau)}\,\sqrt{R\Omega(\tau)R'}\,N\left(0,I_q\right) \qquad (6)$$

For given $\tau-\mathrm{th}$ quantile, the Wald statistics of testing $\beta_T(\tau)=0$ is:

$$W_T(\tau)=T\hat{\beta}_T(\tau)'\frac{1}{R\hat{\Omega}(\tau)R'}\frac{\hat{\beta}_T(\tau)}{\tau(1-\tau)} \qquad (7)$$

where $\widehat{\Omega}(\tau) = \hat{f}[F^{-1}(\tau)]^2 \widehat{M}_{zz}{}^{-1}$ is a consistent estimator of Ω. $\hat{f}[F^{-1}(\tau)]$ is a consistent estimator of $f[F^{-1}(\tau)]$. $\widehat{M}_{zz} = T^{-1} \sum_{t=1}^{T} z_{t=1} z'_{t=1}$ is a consistent estimator of M_{zz} .

According to Koenker and Machado (1999) advice, supremum-Wald test is used here to test (4). The supremum-Wald statistic is:

$$\sup W_T = \sup W_T(\tau_i),\ \tau \in (0,1) \tag{8}$$

The critical values of supremum-Wald test is given by Andrews (1993).

Table7: The critical values of sup-Wald test

	q=1		q=2		q=3	
	5%	1%	5%	1%	5%	1%
0.50	3.84	6.63	5.99	9.21	7.81	11.34
0.40	6.57	9.82	9.02	12.91	11.17	14.88
0.30	7.51	10.91	10.19	14.16	12.58	16.24
0.20	8.45	11.69	11.26	15.09	13.69	17.28
0.10	9.31	12.69	12.27	16.04	14.62	18.28
0.05	9.84	13.01	12.93	16.44	15.15	19.06

4. Empirical Study

This paper focus on how do the new systemic risk measures predict the uncertainty shocks at the micro, macro and higher-order level. The introduction of these measures and the uncertainty shocks are in part 3. This part mainly discuss the Granger-causality in quantile regression to invest potentially nonlinear dynamics the uncertainty shocks and the systemic risk measures. This method can show the distribution in different quantiles which contain more rich information.

4.1 Ststistics of the uncertainty shocks and the systemic risk measures

To start, the statistics information of these measures are summarised in table8.

Table8: Statistics of the uncertainty measures and the systemic risk measures

		Mean	Minimum	Maximum	Standard deviation	Skewness	Kurtosis	Jarque-Bera test		ADF test	
								JB tset	P-value	ADF	P-value
Uncertainty	micro	0.012	-0.233	0.511	0.115	0.907	4.912	57.888	0.000	-7.414	0.000
	higho	-0.014	-0.292	0.396	0.134	0.359	2.886	3.808	0.149	-3.915	0.002
	macro	-0.005	-0.241	0.322	0.100	0.796	3.702	24.991	0.000	-3.017	0.033
Systemic risk	absorption_q	0.560	0.303	0.831	0.111	0.447	2.605	11.787	0.003	-3.489	0.016
	aim_q	0.041	0.004	0.200	0.037	1.609	5.827	234.254	0.000	-6.427	0.000
	covar_q	0.020	0.007	0.062	0.008	1.876	8.085	519.235	0.000	-4.230	0.001
	Δcovar_q	0.008	0.002	0.032	0.005	1.979	8.479	594.169	0.000	-3.475	0.009
	mes_q	0.022	0.005	0.096	0.015	2.218	11.141	1154.480	0.000	-4.031	0.007
	mes_be_q	0.030	0.017	0.056	0.006	0.942	5.959	163.598	0.000	-6.920	0.000
	book_lvg_q	0.000	-0.012	0.010	0.001	-0.598	14.140	889.300	0.000	-10.769	0.000
	catfin_q	0.051	0.022	0.176	0.026	2.450	13.860	1855.697	0.000	-4.982	0.000
	dci_q	0.104	0.009	0.268	0.053	0.776	3.409	36.953	0.000	-4.212	0.001
	def_spr_q	1.050	0.353	3.023	0.533	1.377	4.613	132.509	0.000	-3.465	0.009
	Δabsorption_q	0.098	-0.183	0.257	0.069	-0.813	5.750	93.306	0.000	-9.268	0.000
	intl_spillover_q	0.010	-12.033	10.433	1.422	-0.142	15.400	1211.561	0.000	-16.997	0.000
	gz_q	0.010	-0.733	1.013	0.146	1.442	21.064	2105.496	0.000	-5.228	0.000
	size_conc_q	0.005	-0.156	0.654	0.068	1.956	17.977	3115.390	0.000	-15.347	0.000
	mkt_lvg_q	-0.005	-1.365	1.494	0.232	4.887	10.031	26.756	0.000	-11.522	0.000
	real_vol_q	0.017	0.009	0.065	0.007	3.056	19.657	3634.997	0.000	-4.338	0.000
	ted_spr_q	1.573	-59.970	69.853	11.670	0.608	19.250	1194.891	0.000	-13.251	0.000
	term_spr_q	1.470	-1.407	4.003	1.120	-0.095	2.416	3.674	0.067	-3.198	0.020
	turbulence_q	22.917	3.030	218.602	18.328	5.144	45.577	27500.049	0.000	-7.542	0.000

From table, the kurtosis of all measures are positive, and most of them are right_skewed except book leverage, def_spr, Δ absorption,intl spillover and term_spr. The statistics of JB test of high-order indicates that the variable is normally distributed. The rest of measures do not follow normal distribution on 99% confidence level except that term_spr_q is not normally distributed on 90% confidence level. The original data of Book leverage, intl_spillover, gz, size_conc, mkt_lvg, ted_spr do not pass the ADF test, so I process the data through first difference to have stationary series, because the stationarity of the series is the precondition of the next causality test. From the ADF test results in table, all the measures are the stationary series.

4.2 Sup-Wald tests on causality of uncertainty shocks & systemic risk measures

For each uncertainty shocks-systemic risk measures, contruct the models as below to do the estimation:

$$u_t = \alpha_0(\tau) + \sum_{i=1}^{p} \alpha_i(\tau) u_{t-i} + \sum_{j=1}^{q} \beta_j(\tau) s_{t-j} + e_t \tag{9}$$

$$s_t = \alpha_0(\tau) + \sum_{i=1}^{p} \alpha_i(\tau) s_{t-i} + \sum_{j=1}^{q} \beta_j(\tau) u_{t-j} + e_t \tag{10}$$

where u_t is the uncertainty shocks and s_t is systemic risk measures. (10) is the reversed causal relations. Because the Granger-causality test is sensitive to the lag, in order to get stationary result, according Davidson and Mackinnon (1993), I firstly set a maximum lags $q_{max} = 3$ with τ in [5%, 95%] and use sup-Wald test to check whether to reject the null hypothesis. If q_{max} does not reject the null hypothesis with τ in [5%, 95%] then the appropriate q: $q_* = q_{max} - 1$ and test again until find the q_* with the most significant sup-Wald test statistics.

To get the sup-Wald statistics, set a quantile range $\Gamma = [0.05, 0.95]$, then choose 10 points $(0.05 = \tau_1 < \cdots < \tau_n = 0.95)$ and calculate the Wald statistic of each point and choose the maximum and compare with the Sup-Wald test critical values. The sup-Wald test critical values are shown in Table 7. The sup-Wald test results are shown in 9, 10 and 11.

Table9: The sup-Wald test results of non-causality on micro & systemic risk measures.

Systemic measures effects on Micro uncertainty	lag=1	lag=2	lag=3
covar	11.94**	19.14**	8.50
book_lvg	16.74**	5.77	8.55
gz	32.78**	8.66	1.89
ted_spr	8.16*	15.1**	17.10**
catfin	4.58*	7.63*	6.40
turbulence	9.81*	3.24	3.01
dci	11.31*	1.86	6.14
def_spr	9.05*	2.79	2.72
mes	8.72*	5.06	7.47
absorption	8.41*	9.45	8.71
real_vol	7.30	15.92*	7.18
intl_spillover	2.92	2.67	4.30
Δ covar	4.09	2.66	3.62
mes_be	3.82	4.09	5.60
aim	3.65	6.63	7.70
term_spr	5.85	4.63	5.24
mkt_lvg	3.09	1.83	3.19
Δ absorption	2.77	2.56	1.43
size_conc	2.96	4.88	3.49

Notes: ** and * indicates 99% and 95% confidence level respectively.

Table 10: The sup-Wald test results of non-causalityonmacro & systemic risk measures.

Systemic measures effects on Macro uncertainty	lag=1	lag=2	lag=3
gz	4082.20**	3.09	103.32**
covar	21.64**	4.96	10.23
mes_be	18.84**	4.07	8.35
mkt_lvg	7.50**	10.22	10.97
absorption	11.84**	8.49	6.49
ted_spr	10.77**	4.22	4.92
def_spr	8.76*	9.37	6.80
real_vol	6.46	4.30	8.02
book_lvg	3.96	4.49	6.35
dci	5.95	5.59	5.27
aim	4.56	4.33	3.91
mes	3.53	3.05	2.84
Δ covar	4.76	3.99	2.18
catfin	8.33	2.68	6.14
turbulence	2.83	8.14	2.67
intl_spillover	5.92	3.78	3.53
term_spr	2.26	5.62	4.44
Δ absorption	4.30	7.59	4.69
size_conc	2.06	2.62	1.98

Notes: ** and * indicates 99% and 95% confidence level respectively.

Table11: The sup-Wald test results of non-causality on high-order & systemic risk measures.

Systemic measures effects on Higher-order uncertainty	lag=1	lag=2	lag=3
ted_spr	13.36**	6.93*	10.86
covar	17.28**	11.15*	9.50
book_lvg	9.67*	10.93*	10.35
absorption	10.67*	12.56*	7.67
turbulence	6.03*	7.38*	5.01
gz	11.4*	1.62	14.82*
Δ covar	6.97*	6.84	7.84
aim	6.81*	4.24	2.80
size_conc	3.27	9.16*	6.71
mes_be	6.51	11.48*	13.81*
Δ absorption	4.70	3.51	3.16
dci	7.45	5.36	6.27
def_spr	2.07	2.83	6.14
real_vol	7.39	4.93	5.91
mes	3.10	4.04	2.31
catfin	2.28	2.80	2.57
intl_spillover	3.06	5.87	6.82
term_spr	2.27	1.95	1.69
mkt_lvg	3.78	2.33	1.11

Notes: ** and * indicates 99% and 95% confidence level respectively.

As table 11 shows, first lagged Covar, Book_Leverge and GZ granger cause Micro on 99% confidence level. First lagged Ted_Spr, Catfin, Turbulence, DCI, Def_Spr, MES and Absorption granger cause Micro at 95% confidence level. Second lagged Real_Vol granger causes Micro at 95% confidence level.

From table9, the first lagged GZ, Covar, MES-BE, Mkt_Leverge, Absorption and Ted_Spr granger cause macro level on 99% confidence level while first lagged Def_Spr granger causes macro level on 95% confidence level.

From table 10, the first lagged Ted_Spr and Covar granger cause higher-order level on 99% confidence level while first lagged Book_Levergr, Absorption, Turbulence, GZ, Δ Covar and AIM granger cause higher-order at 95% confidence level. Second lagged Size_Conc and MES-BE granger cause higher-order at 95% confidence level.

4.3 Quantile regressions

This paper aims to find how the systemic risk measures predict the uncertainty shocks on micro, macro and higher-order level, so I run the quantile regressions under a high bound using those lagged systemic risk measures which granger cause uncertainty shocks on 95%

or 99% confidence level to show their distribution in different quantiles. I choose different lags for different measures to do the quantile regressions respectively according to the results shown in table 9, 10 and 11. If first lagged and second lagged or third lagged all have significant effects, the most significant regression result will be used. The reason why testing under a high bound because this paper focus on the systemic risks measures effects on uncertainty shocks which is second moment, this process is more related to the marginal effect. What's more, the comparisons between 0.5^{th} quantile and 0.85^{th} quantile of each relation are also given in table 15. The estimated coefficients of quantile regressions are shown in table 12, 13 and 14.

Table 12: The 0.85^{th} quantile regression coefficient estimates of systemic risk measures on micro.

85th Systemic risk measures effects on micro	β 1	β 1 using OLS	α 0	α 1	R^2
turbulence	0.00*	0.00**	0.07*	0.41**	0.17
Covar	4.40*	1.93*	0.01	0.40**	0.14
book_lvg	-9.93*	-4.18	0.11**	0.53**	0.16
absorption	0.24*	0.17*	-0.02	0.40**	0.15
catfin	1.85*	1.06**	0.04	0.23	0.16
mes	0.41	1.35*	0.10*	0.55**	0.14
gz	0.13	0.06	0.11**	0.46**	0.16
ted_spr	0.00	0.00	0.12**	0.56**	0.22
dci	0.14	0.24	0.11**	0.52**	0.14
def_spr	-0.04	0.00	0.16**	0.51**	0.13
real_vol(2)	3.85	1.48	0.04	0.49**	0.15

Notes: ** and * indicates 99% and 95% confidence level respectively. (2) means second lagged, the others are first lagged.

The OLS estimated β of Turbulence, Covar, Absorption, Catfin and MES are larger than 0 significantly while Book_Lvg, GZ, Ted-Spr, Real_Vol, DCI and DEF-SPR are insignificantly. The quantile regression estimated β of Turbulence, Covar, Book_Lvg, Absorption and Catfin are significant at 0.85^{th} quantiles. Only the Book_Lvg's coefficient is negative.

Table 13:The 0.85th quantile regression coefficient estimates of systemic risk measures on macro.

Systemic risk measures effects on macro	β 1	β 1 using OLS	α 0	α 1	R^2
mkt_lvg	0.05**	0.05*	0.06**	0.89**	0.49
covar	-0.37	3.38**	0.06*	0.89**	0.46
def_spr	-0.03	-0.03**	0.08**	0.94**	0.47
gz	-0.09	0.10	0.05**	0.95**	0.48
mes_be	-1.13	2.80	0.09	0.90**	0.46
absorption	0.14	-0.05	-0.03	0.92**	0.47
ted_spr	0.00	0.00	0.06**	0.96**	0.49

Notes: ** and * indicates 99% and 95% confidence level respectively. All of them are first lagged.

The OLS estimated β of Mkt_Lvg, Covar and Def_Spr aresignificant while others are insignificant. The quantile regression estimated β of Mkt_Lvg is significant at 0.85th quantiles showing positive relation while others are insignificant.

Table 14: The 0.85th quantile regression coefficients estimates of systemic risk measures on high order

Systemic risk measures effects on high-order	β 1	β 1 using OLS	α 0	α 1	R^2
covar(2)	-2.49**	-1.50*	0.13**	0.76**	0.38
mes_be(2)	-5.43**	-1.89	0.36**	0.79**	0.40
Δ covar	-3.19*	-2.31	0.12**	0.77**	0.38
gz	0.17*	0.05	0.89**	0.70**	0.39
size_conc(2)	0.05	-0.33*	0.09**	0.82**	0.38
ted_spr	0.00	0.00	0.09**	0.74**	0.37
aim	0.69	0.45	0.09**	0.80**	0.38
absorption	-0.07	-0.04	0.13*	0.79**	0.38
book_lvg	0.21	1.02	0.09	0.78	0.37
turbulence	0.00	0.00	0.09	0.78	0.37

Notes: ** and * indicates 99% and 95% confidence level respectively. (2) means second lagged, the others are first lagged.

The least-squares estimated β of second lagged Covar and Size_Conc are smaller than 0 significantly while others are insignificant. The quantile regression estimated β of Δ Covar , COVAR and MES-BE are significant at 0.85th quantiles, showing negative relations with higher-order uncertainty shocks on higher tail. GZ's coefficient is positive at 0.85th quantile significantly.

I also test whether the causal effects at the 0.5th and 0.85th quantiles have the same weight and obtain a confidence interval for the difference. But the result does not show the significant difference.

Table 15: The difference between 0.5 th and 0.85 th quantiles

		Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
	covar	2.78	2.42	1.15	0.25	-2.00	7.56
	book_lvg	-7.34	5.49	-1.34	0.18	-18.18	3.50
	gz	0.10	0.12	0.84	0.41	-0.14	0.34
	ted_spr	0.00	0.00	0.22	0.82	0.00	0.00
	catfin	0.91	1.00	0.91	0.37	-1.07	2.88
~→Micro	turbulence	0.00	0.00	0.76	0.45	0.00	0.00
	dci	-0.20	0.26	-0.76	0.45	-0.72	0.32
	def_spr	-0.05	0.03	-1.74	0.08	-0.12	0.01
	mes	-1.28	1.87	-0.69	0.49	-4.97	2.41
	absorption	0.06	0.11	0.52	0.60	-0.17	0.29
	real_vol	2.62	2.44	1.08	0.28	-2.19	7.44
	gz	-0.08	0.09	-0.87	0.39	-0.27	0.10
	covar	1.02	1.35	0.76	0.45	-1.64	3.68
	mes_be	-0.02	1.20	-0.02	0.99	-2.38	2.34
~→Macro	mkt_lvg	0.04	0.02	2.51	0.01	0.01	0.07
	absorption	0.17	0.08	2.26	0.03	0.02	0.33
	ted_spr	0.00	0.00	-1.48	0.14	0.00	0.00
	def_spr	0.00	0.03	-0.09	0.93	-0.06	0.05
	ted_spr	0.00	0.00	1.26	0.21	0.00	0.00
	covar	-1.20	1.13	-1.07	0.29	-3.43	1.03
	book_lvg	1.91	5.37	0.36	0.72	-8.68	12.50
	absorption	0.00	0.09	0.01	0.99	-0.19	0.19
~→Higher-order	turbulence	0.00	0.00	1.03	0.30	0.00	0.00
	gz	0.12	0.09	1.33	0.18	-0.06	0.31
	Δ covar	-1.71	1.85	-0.93	0.36	-5.37	1.93
	aim	0.36	0.87	0.41	0.68	-1.35	2.08
	size_conc	0.45	0.28	1.59	0.11	-0.11	1.01
	mes_be	-2.09	1.53	-1.36	0.18	-5.13	0.94

Notes:~ means the systemic risk measures

5. Conclusion

This paper examines how systemic risk measures predict the uncertainty shocks on micro, macro and higher-order level. I mainly use the granger causality on quantile regression to find the relations under a high bound between each of them. The results show that not all of the lagged measures have significant effect on capturing the uncertainty shocks information.

Among these measures, first lagged Covar, Book_Lvg, Absorption, Catfin and Turbulence can significantly reflect the higher tail of the uncertainty shocks on micro level. Book_Lvg has significant negative relations while others are positive. It shows that the measures of volatility can captures more information about uncertainty shocks on micor level because Book_Lvg, Catfin and Turbulence are all relates to the volatility and instability.

First lagged Mkt_Lvg has significant effects on uncertainty shocks on macro level in 85^{th} quantile and has a positive relation with uncertainty shocks on macro level. However others do not show significant effects. The macro uncertainty shocks are more complicated and varied, so it is reasonable that individual measure cannot predict the shocks on macro level well. Constructing a index based on all the measures may have better prediction.

Second lagged MES-BE, Covar, Δ COVAR and GZ has significant effects on uncertainty shocks on higher-order level at 0.85^{th} quantiles and most of them show negative relations. Because higher-order uncertainty relates to firms different forecasts when firms disagree according to Nicholas et,al. MES-BE, Covar, Δ COVAR all relates to institution-specific risks, so it is reasonable that higher-order uncertainty shocks' information can be captured by institution specific well. The negative relation means that the exacerbation of crisis will narrow the disagreements among firms.

Because these new systemic measures actually have some overlaps, so further analysis can choose typical models of them or construct an index to see how they can predict the uncertainty shocks. What's more, if the test can be done on different specific period of crisis, then the results would be more significant.

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