Empirical Study of the Connection of Media Attention and Bank's Operating Risk in United States

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Abstract. Public opinions were proved to have effects on the financial risk. According to the previous theoretical explanations about the impact of polarized opinions on financial market, media attentions, as one of the primary representative indexes in public opinions, was assumed to be associated with financial risk by gathering warning information from various channels in markets. By introducing data of GDELT from Google, media attention was quantified as the frequency of reports containing certain keyword. The operational risk of U.S. banks was quantified by NPLs as used in numerous previous studies. Various regression models were set for analyzing the connection of media attention to the operational risk under a group of controlled macroeconomic parameters. Robust results were obtained from the above estimations supporting the early assumption on connecting media attentions to risk. In addition, the outcomes of the above quantitative analysis displayed the heterogeneous effects of media attention on risk of banks with different asserts.

Keywords: Media Attention · Financial Risk · Bank · NPLs

1 Introduction

Numerous researchers have studied the impact of public opinions on the financial markets. The mutual influencing mechanism between public opinions and financial markets were summarized in an interacted process. Polarities of people's opinions orientate the convergent behaviors of majority in financial markets [17], reshaping the supply and demand of financial assets. Consequently, the price of assets fluctuates, generating various potential risks. Previous studies were proved to connect public opinions as a cause to systematic financial risk [5]. In opposite, according to the mutual influencing process with financial assets, public opinions may be the aggregated responses of majority to the upcoming market crisis, which were rare focused by researchers.

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The sources used for academic research can be generally categorized into two types, social media and traditional media [6]. Traditional media (i.e., Newspaper, Journals, Publications) commonly contains attitudes of certain representative groups with parts of the total public opinions. Research of public opinion related to traditional media can be traced back to ancient Greece [15]. Given the incomplete coverage of certain publications in traditional media, it needs large bulks of efforts to collect data from vast media sources with the purpose of reaching the nature of public opinions [3]. To reduce the difficulties in data collection, most previous studies in traditional media employed questionnaires to capture the sentiment of specific groups instead of analyzing all accessible publications [10], which accentuated the bias in sample selection. With the rise of internet and computer applications, more personalized opinions can be identified via a new type media, i.e., social media. Though the appearance of social media provides new accessible sources for research, it does not depreciate the values of traditional media, which remain an unsolved challenge with flaws in coverage of bias.

The goal of more accurate and representative public opinion by the integration of social media and traditional media were not accomplished until the recent outbreak of computer power and its application in big data [6]. Through the mass storage and computer power, worldwide searching engine could generate integrated results with minimum biased coverage by capturing information from all available sources in both social and traditional media, providing more reliable and detailed data for quantifying the media attention by topics.

The application of media attention to financial markets are growing with the outbreak of the internet and big data [14]. Most of these application focus on combating the potential financial risk, including four major types of risk, i.e., Liquidity risk, credit risk, market risk, and systematic risk [8]. Risk during operation of financial institutions receives less attention despite of the close connection to the all types of risk above. Major methods used for past operational risk analysis of financial institutions employed economic indicators in social statistics [9].

In risk research, media attention could be considered as a new indicator which was widely used in other areas to replace the common indicators. There are two issues tried to be explored in this paper by applying media attention as new indicator: (1) media attention is a valid indicator for causality analysis for operational risk. (2) media attention reflects the early social awareness of upcoming risk and envision the potential status of financial operation.

2 Background

2.1 Big Data and Financial Risk

The research of media attention's impact on financial risk is one of potential applications in big data. Targeting at major types of risk, technologies integrated with big data improve the risk management of financial institutions in the extraction of representative data [12], establishment of users' behavior modeling [18], construction of knowledge graph on business or clients [13], and analysis with Natural Language Processing (NLP). With the assistant of modern technologies in big data, financial institutions are able to set up a new system of risk management by embedding user profile, network connection of companies, behavior pattern of clients, and other extracted information from multi-model data. The new system helps financial firms to combat potential risk and crisis in early warning of upcoming defaulted items, identification of fraud and theft, and prevent of money laundering. Although numerous reports showing the growing revenues in firms working on combining big data, and financial services [4], it is still lacking of direct evidences proving the effectiveness in combating the risk of such investments. As one of the major applications in big data, the proved connection of media attention and operational risk could partially support beneficial exercise of big data.

2.2 Nonperforming Loans as Operational Indicator of Financial Risk

Many operational indicators were studied to measure the risk of financial institutions. Among these indicators, nonperforming loans are one of key indicators widely used in most evaluations by supervisory authorities and academic institutions. NPLs are referred to loans of which borrowers fail to provide payments due over 90 days or more, inferring the potential default loss. As a disfavored, but inevitable side effect of business on credit and loans [11], nonperforming loans (NPLs) link closely to the managerial capacity of financial risk and are appropriate indicators for evaluating business operations [1]. Various studies were conducted to analyze the related contents of NPLs, most of which concentrate on the determinants of NPLs [7], causality of NPLs [2], and assessment of financial institutions by NPLs.

The NPLs' determinants from early researches can be classified in two categories. The first category contains determinants from macroeconomics, e.g., Gross Domestic Production (GDP), Money Supply, Unemployment Rate, Inflation Rate, and Lending Interest Rates. The second category is often referred as bank specific determinants, including those factors tightly tied to the operation of bank [16]. Previous studies also displayed determinants varied as banks operating in different economies and business models. Consequently, performances of NPLs and related operational risks in banks differ significantly.

3 Hypothesis and Methodology

3.1 Hypothesis

In this paper, a new indicator with big data and media is introduced to test the theory that mutual effects exist between public opinion and financial risk. By recording opinions from social individuals, public opinions could be treated as a vault of mass information from all possible channels. Thus, valid information for warning an upcoming financial risk in the market is included, which ties firmly to the potential operational risk in financial institutions, accounting for the NPLs' generation in banks' operations. In the past, limited by technology and potential huge workload, the whole of public opinions was partially accessed by past researches. Among all types of samples collected for research, media opinion was the relatively good one compared to questionnaires and others.

In 2016, Google launched a project, named as a Global Database of Events, Language, and Tones (Henceforth GDELT). GDELT executes real-time monitoring globally over the all-accessible reports, press, news as well as other types of media contents for specific events. The database provides statistical results of frequency on certain keywords by sort of time and language, indicating the media attention on selected topics. Considering the relations of media attentions and bank differing by the structure and development of individual economy, this paper focuses on the exploration of such relation in the United States.

As an indicator of public opinions, the effective information from media attention differs by targets. There would be more information leaked out to the market and society for commercial clients than non-commercial clients. It is inferred that media attentions could better fit in commercial loans as contrast to non-commercial loans.

In summary, the paper proposed the following hypotheses.

Hypothesis I: The frequency given by the keywords "financial risk" via GDELT matches the trends of operational risk in banks as indicated by NPLs.

Hypothesis II: The frequency given by the keywords "financial risk" via GDELT impacts differently on commercial and non-commercial indicators.

3.2 Methodology

3.2.1 Data and Variables

Data for Media Attentions are collected by Google GDELT as the input keyword "Financial Risk" and are listed as reported frequency over time.

Data for bank specific factors are provided by U.S. Federal Reserve Economic Database (FRED). The ratio of NPLs to total loans with conditions is key variables used to inspect the interactions between media attention and financial risk. To demonstrate the variability between bank scale, as classified by the U.S. Federal Reserve, there are two representative groups of banks collected in this study. From the least in scale with the greatest in scale, the above bank groups are banks with assets with assets between 300 million - 1 billion, and banks with assets over 20 billion. Besides the bank groups, several other groups are chosen to further explore the potential difference among banks with the variance in their major clients. These groups are total NPL/Total Loan (TL) ratio of all banks, NPL/TL ratio in the commercial sector, total NPL of all banks in USD, and total commercial NPL of all banks in USD.

Data for U.S. macroeconomics are from worldbank and FRED. Referring to the previous studies, the following variables are selected, GDP, growth rate of GDP, unemployment rate, M2 money supply, the growth rate of M2, and Consumer Price Index (CPI).

Since GDELT was established in fall 2016, all data begin at Jan 1st 2017 inconsistent with GDELT. To avoid the disturbance of systematic strike from the unexpected event outside society, i.e., the unprecedented outbreak of Covid-19, data collected stop at Jan 1st 2020. All data used are adjusted quarterly as time series.

3.2.2 Quantitative Model

As shown in previous studies, without the consideration of media attention, the causation of NPLs as an indicator of banks' operational risk was measured by several quantitative models, most of which were dynamic models integrated with parameters from macroeconomics and bank specific sectors. In this paper, the primary goal is to discuss the facts of general trends in banks' operational risk with media attentions, setting aside those bank specific parameters. Thus, the research method is simplified only with macroeconomic parameters, which are set as control variables (Table 1).

Since the media attention is a new introduced variable, in this paper, two types of NPLs' variables are selected to test the hypothesis of the existence of differences. The first was the variable from those small banks with assets 300M-1B as the second one consisting of large banks with assets over 20B.

As the interest of the Federal Reserve Fund and CPI are parameters tightly associated with money supply, the two parameters of FRED and CPI are used as replacements of M2 money supply to test the robustness of econometric models. Unemployment Rate is used as replacement of GDP related parameters.

The econometric model is set as below:

$$RBs = \alpha + \beta * M_i x + \mu + \varepsilon \tag{1}$$

where RBs represent the list of variables in Risk of Banks, α is the constant, Mi gives the combination of macroeconomic parameters, μ symbolizes those unobserved factors, and ε is the error. Pointed out by the previous research, data for time series usually contain problems of heteroscedasticity and autocorrelation. Various tests were employed to identify the existence of the above potential problems.

4 Estimation Results

4.1 Heteroscedasticity and Autocorrelation

In To obtain the robust estimation of heteroscedasticity in the key variable, a two-step generalized least squares (GLS) method was executed for the model with np2tl as dependent variables, firac as independent variables, and gdp & M2 as controlled variables. The two-step GLS began with the estimation of residuals in ordinary least squares (OLS) method. For the independent variable with heteroscedasticity, the second step constructed a variable of variance as the exponential form of residuals and estimated the final results with adding the new introduced variance. The results of two-step GLS sent for the likelihood ratio (LH Ratio) test, which compares the results from OLS and two-step GLS to display the significance of heteroscedasticity. As indicated by the Table 2, Chi square of LH ratio test did not reject the null hypothesis of existence of heteroscedasticity. Thus, heteroscedasticity in data of firac may not be a significant problem, inferring OLS with robust a better method fitting the model.

By assuming the errors with first order autocorrelation, the same model of heteroscedasticity was tested through the application of Cochrane-Orcutt's method. The Durbin-Watson statistics from both original and transformed estimations present the potential autocorrelation. In this test, the result of original estimation was greater than the transformed, indicating minor autocorrelation (see Table 2).

In summary, the selected data showed minor problems in heteroscedasticity and autocorrelation. Thus, the following estimations were all based on OLS with robust standard errors.

Table 1. Data and variables.

Risk of Banks	Note	Macroeconomics	Note	Media attention	Note
NP2TL	total NPLs to total loans for all banks	GDP	Gross Domestic Production	Financial Risk	Frequency listed by GDELT
NPCD	total NPLs in commercial sector for all banks	GDPrate	Growth Rate of GDP		
NP2TLSM	total NPLs to total loans for banks with 300M-1B	M2	M2 Money Supply		
NP2TL20B	total NPLs to total Loans for banks over 20B	M2rate	Growth Rate of M2		
		UN	Unemployment Rate		
		FRED	Interest Rate of Federal Reserve Fund		
		CPI	Consumer Price Index		

4.2 Results of Media Attention

Shown in Table 3, coefficients of firac obtained for np2tl and npcd were significant with GDP and M2 as well as their growth rate. As changing controlled variables to CPI, Fed, and Unemployment, coefficient of firac obtained for np2tl was relatively significant, and that for npcd was not. By comparing the different tests, it was inferred that media attention generated their major influences on macro markets as significant changes occurring for the total NPLs. From the different results given by nptl20b and nptlsm, it clearly presented more effectively influence of media attentions on larger banks than smaller banks, which was in line with the results of the macro markets.

Among the controlled parameters, GDP was the most effective and significant one, in agreement with the previous studies. It is inferred that media attentions create connection to financial risk by gathering information leaked from macroeconomic condition, which affected the operations in recipients of NPLs in banks. Next to GDP, it is CPI, which is symbolic of the growth of the money supply over the production of commodities, encouraging the quickly expand of the economy and a better environment of the operations in NPLs' recipients. M2 and fed are two parameters directly associated with money supply by excluding their economic effects which are included in GDP and CPI.

Table 2. Tested results of heteroscedasticity and autocorrelation

	(1)	(2)	(3)
VARIABLES	np2tl	np2tl	np2tl
firac	0.0715*	0.0786**	0.0876*
	(0.0382)	(0.0322)	(0.0521)
gdp	−3.926***	−3.879***	−3.619***
	(0.300)	(0.259)	(0.380)
m2	0.896**	0.895***	0.649**
	(0.307)	(0.261)	(0.328)
Constant	32.13***	31.61***	31.30***
	(2.593)	(2.253)	(2.767)
Observations	12	12	12
R-squared	0.987	0.986	
e(dw)		2.053	
e(dw_0)		2.106	
e(p_c)			0.182
e(chi2_c)			1.784

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3. Tested results for media attention.

	1	2	3	4		5	6	7	8
VARIABLES	np2tl	nptl20b	np2tlsm	npcd	VARIABLES	np2tl	nptl20b	np2tlsm	npcd
firac	0.0715**	0.0991*	−0.0102	0.0761**	firac	0.542***	0.603***	0.114**	0.376***
	(0.0382)	(0.0468)	(0.0773)	(0.0326)		(0.0586)	(0.0661)	(0.0458)	(0.0427)
gdp	−3.926***	−4.572***	−0.319	−3.084***	gdprate	−0.158*	−0.167	−0.0489	−0.0995
	(0.300)	(0.294)	(0.811)	(0.241)		(0.0839)	(0.0946)	(0.0369)	(0.0614)
m2	0.896**	1.322***	−0.648	1.149***	m2rate	−0.0106	−0.00853	−0.0247***	−0.00326
	(0.307)	(0.337)	(0.872)	(0.269)		(0.0204)	(0.0232)	(0.00705)	(0.0142)
Constant	32.13***	34.28***	11.73***	39.64***	Constant	2.053***	−2.505***	1.402***	15.30***
	(2.593)	(3.032)	(3.387)	(2.139)		(0.492)	(0.556)	(0.363)	(0.356)
Observations	12	12	12	12	Observations	12	12	12	12
R-squared	0.987	0.985	0.595	0.981	R-squared	0.817	0.811	0.742	0.801

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Consequently, M2 and fed are not effective or significant as GDP and CPI. A better economic environment reflected by media attentions reduces the NPLs.

Table 4. Tested results for alternative variables.

	1	2	3	4
VARIABLES	np2tl	nptl20b	np2tlsm	npcd
firac	0.0581*	0.0759**	0.0133	0.0492
	(0.0252)	(0.0315)	(0.0678)	(0.0272)
cpi	−6.720***	−7.558***	3.665	−4.043**
	(1.428)	(1.713)	(3.059)	(1.438)
fed	−0.0556*	−0.0828**	0.00534	−0.0544**
	(0.0275)	(0.0275)	(0.0632)	(0.0183)
un	−0.212	−0.387	1.326	−0.104
	(0.319)	(0.369)	(0.773)	(0.355)
Constant	49.57***	56.03***	−28.25	46.63***
	(11.11)	(13.33)	(23.67)	(11.33)
Observations	12	12	12	12
R-squared	0.991	0.990	0.646	0.986

5 Conclusion

By collecting the reported frequency from the GDELT of Google, a key component of media attention with keywords "Financial Risk" was introduced to the quantitative models based on the previous studies. Several parameters from macroeconomics were selected as controlled variables to test the effectiveness of hypotheses.

Results shown in Tables 3 and 4 generally supported the hypothesis I, that media attentions accounted for the production of NPLs. In line with the previous studies, GDP was the most important determinants of NPLs, accounting for over 10% of NPLs in the designed model. M2 accounted for 2.7% at 2% from the media attention. Estimations by different sets of the controlled variables exhibited the heterogeneous effects of media attention on banks with different scales, which was proposed by the hypothesis II.

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