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"NDSM RISK" PRIMER OF THE CANADIAN FINANCIAL INSTITUTIONS AND INSURANCE SECTOR

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Abstract:
To measure the non-diversifiable systemic market risk (NDSM Risk) of the Canadian financial sector is the primary and major focus of conducting this research. In this study, the Non-diversifiable Systemic Risk or NDSM Risk methodology is undertaken to measure systemic risk of the Canadian banks and Insurance companies. The study shows the numerical value of computational table to demonstrate the NDSM Risk for the Canadian Banks and Canadian insurance industry measured in currency value of Million CAD (Worldwide Crises). Here the NDSM Risk methodology is undertaken to carry out this investigation. Lack of resource of primary data is the main creating hindering effect that is faced in this study. This article portrays the increase in unavoidable risk factors leading to consequences of aggregate sovereign risk also accelerating these problems within the regions and countries mentioned in this research. Due to the COVID-19 outbreak, the developed nations as well as emerging economies are facing vulnerability in the area of financial, governmental, environmental in order to be Financially resilient. This is high time of detecting these problems and taking precautionary measures by the policy-makers and government in the economic sector by adopting implementable methodologies. The current study reflects the situation with regard to forthcoming researchers who intends to study as well as interested in this particular area.

Keywords: Financial Risk, Insurance Sector, Banking Industry, Global Crises, Canada

1.INTRODUCTION

The unfavorable effects of the 2007 to 2009 financial crisis highlighted significantly the necessitate to identify a well as more heavily standardize financial institutions whose breakdown would have important negative sequential consequences for both financial and the real sectors according to the economy. As opposed to the firm's individual risk in regard to failure, which can be substantially contained without creating harm to the whole or entire system, Non-diversifiable Systemic Market Risk (NDSM Risk) is the risk regarded as the collapse of an aggregate or entire financial system and market. In this paper, as a sequential chronology, this study investigates as well as modify the NDSM Risk measure in regard of the Canadian sector of banking as well as insurance institutions.

The NDSM Risk measure is also defined as the expected shortfall of capital of a firm on basis of conditional on a lengthened market based decline. The simplicity as well as transparency of the NDSM Risk measure makes this particularly attractive in regard of analysing the NDSM Risk of the financial institutions. NDSM Risk is a function in regard of the institution's leverage, size, and expected equity loss conditional in regard to the market decline, which is also referred to as the Long-Run Marginal Specific Expected Shortfall (LRMSES). This study implements a GARCH time series model with regard to estimate LRMSES using the Bloomberg data from January 3, FY2000 to June 30, FY2016.

This paper executes the following kind of four contributions. First, we portray that the segregated funds ought to be excluded from particularly the debt of the insurance companies. Indeed, both on the basis of considering Generally Accepted Accounting Principles (GAAP) as well as International Financial Reporting Standards (IFRS) in regard of insurance companies necessitate segregated funds in order to be incorporated with the balance sheet (both as an asset as well as a liability). However, the worth of the segregated funds is in the long run the value of aggregate underlying mutual fund as well as is distinct comparing to the actuarial liability with regard to the policyholder's assurance on the particular segregated fund. The NDSM Risk methodology's insertion of the segregated funds as the liability gives a mislead impression of the high leverage with regard to insurance companies as well as due to the chronological significant size with regard to segregated funds which translates to a substantial measure of overestimation of NDSM Risk values. For example, the expected shortfall of capital of Hartford dated on June 30, FY2016 was estimated particularly as 8 billion USD exclusive of the adjustment for the specific segregated funds. However, the expected shortfall of capital becomes zero during segregated funds significantly are accounted for.

Second, we estimate on basis of prudential based capital measure ratio that ought to be used for the Canadian firms. Since US firms significantly report under the US GAAP their derivative based holdings are particularly reported as net, whereas Canadian as well as European institutions, who are measured under IFRS, report their assessment of derivatives as the gross. To account on basis of this difference, previous researchers suggested a prudential capital based ratio of 8% for the US companies as well as 5.5% for the European firms. Consequently, it might seem appropriate to use a significant prudential based capital ratio of 5.5% for in regard of Canadian companies. However, Canadian financial institutions are comparatively less active on the basis of the significant derivatives market (than many United States and European based firms) and this analysis particularly shows the assessment that if one value measurement of prudential based capital ratio is to be in near future used for all Canadian financial institutions then the capital ratio of numerical figure 7.5% is more appropriate rather than the value of 5.5%. We would like to further point out that the prudential based capital ratio of the 7.5% may be most suitable for Canadian banks and might be less so with regard to other Canadian firms together with insurance companies. In general, it is rather complicated to pin down the single capital ratio value in favor of all Canadian financial institutions utilising only the remarkable historical prudential based capital ratio measure of analysis.

Third, we portray that NDSM Risk values of the Canadian banks and insurance based companies should not be rather interpreted as being equal towards their expected significant capital shortfall within a crisis. For example, the total NDSM Risk of the top-most five Canadian banks was approximately 80 billion CAD towards the end of FY2008 (more than 5% compared to Canadian GDP) which seems to be somehow at odds along with what was truly observed during that crisis. Canadian financial monetary institutions did not essentially require bailout related funds from the regulatory government body and overall, Canada accomplished a far relatively well achievement during this duration of period. Thus, it seems to be much more appropriate with relevance to the NDSM Risk of Canadian banks a well as insurance companies because their tendency in regard to propensity to being sufferer to face severe losses throughout a financial crisis. Indeed, at the commencement of 2007-2009 financial crisis, Canadian Imperial Bank of Commerce (CIBC) also had high values with regard to NDSM Risk, whereas Toronto Dominion (TD) bank's NDSM Risk was comparatively rather negligible. As it turned out, CIBC experienced outsized losses all through the crisis, while the write-downs of TD's were smaller.

Athey (2017) portrayed the emergence of big data in order to safeguard from policy related problems [1]. Bard et. al (2020) portrayed the Hanabi challenge to make up a solution to crises issues [3]. Benoit et. al (2017) assessed the risk of systemic criteria to forecast the financial sector crises [4]. Brownlees and Engle (2016) demonstrated the Conditional Capital Shortfall Measure of Systemic Risk in thier study [5]. Bianchi et. al (2020) researched the Bond risk premier with machine learning [6]. BlackRock (2019) portrayed the implication of Artificial intelligence and machine learning in asset management to work with crises moments [7]. Bouvard et. al (2020) demonstrated the transparency in the financial system covering the benchmark of rollover risk and crises [8]. Brown and Sandholm (2019) researched regarding the economic crises in their study [9]. Brunnermeier and Peterson (2008) researched regarding the capital liquidity and funding liquidity in the demonstration of research [10]. Bryzgalova (2020) portrayed the study of building cross section stock returns to measure the volatility [11]. Calvano et. al (2020) studied the findings way out to the remedy of distress moments based on studying the artificial intelligence, algorithmic pricing and collusion [12]. Dan´ıelsson (2017) demonstrated the possible remedy to find out the way to the solution of financial crises [14]. Ding et. al (2018) demonstrated the investor-imitator framework for trading knowledge extraction to detect financial distress [17]. Gu et. al demonstrated the research and found the remedy to volatility criteria of empirical asset pricing via machine learning [15]. Hase and Bansal (2020) demonstrated the research regarding the evaluation of explainable AI, which algorithmic explanations help users predict model behavior to detect the distress movements [18]. Hase and Bansal (2020) evaluated the AI in perspective of predicting model behavior [19]. IP (2015) researched the volatility detection moments [20]. Kelly (2016) researched the price of political uncertainty based on the theory and evidence from the option market [21]. Khandani et. al (2011) demonstrated regarding the quant's data evidence from factors and transactions values in the timeline of 2007 onwards [22]. Klein (2020) researched regarding the ways out to reducing bias in AI-based financial services [23]. Dan´ıelsson (2002) researched regarding the endogenous risk within the area of modern risk management [15]. Dan´ıelsson (2018) researched regarding the financial crises [16]. Athey (2019) found out the way by their study by the method to ensemble for causal effects in panel data settings [2]. Cong et. al (2020) described the alpha portfolio investment measure in perspective of AI [13].

2. MATERIALS AND METHODS

The NDSM Risk is defined as the projected capital kind of shortfall of an institution during the period of a financial crisis in this study. To translate the definition of NDSM Risk towards a mathematical specific formula, this study starts particularly with the subsequent definition of the capital kind of shortfall ($\hat{C}\check{s}$) next to time t of the i^{th} type of institution

$$\hat{C}\check{s}_{i,t} = \mathbb{k}\mathbb{A}_{i,t} - \mathbf{E}_{i,t}$$

where $\mathbf{E}_{i,t}$ is the total market price of the firm's equity (named market capitalization), $\Bbbk$ is the prudential kind of capital ratio of the equity to assets, and $\mathbb{A}_{i,t}$ is the "quasi-market specific value" of assets which is,

$$\mathbb{A}_{i,t} = D_{i,t} + \mathbf{E}_{i,t} \qquad (1)$$

with $D_{i,t}$ representing significantly the book value of specific debt. In other words, the firm is considered typical short of the capital when the market value of the equity becomes comparatively smaller than a small number of fraction, $\Bbbk$, of its "quasi" assets. Since we want to compute the systemic risk of significantly an institution, we evaluate particularly the expected kind of capital short-fall ($\mathbf{E}\hat{C}\check{s}\mathsf{F}$) of the institution i throughout a financial economic crisis between the times t and $t+T$, demonstrated as,

$$\mathbf{E}\hat{C}\check{s}\mathsf{F}_{i,t:t+T} = \mathbf{E}_t[\Bbbk\mathbb{A}_{i,t+T} - \mathbf{E}_{i,t+T} | Crisis_{t:t+T}] \qquad (2)$$

where $\mathbf{E}$ is the typical expectation operator. The "systemic" nature of the definition generated from the fact that the capital shortfall is assessed under the typical assumption that the particular financial system is previously in crisis, implying that that bankruptcy of the firm cannot be effortlessly absorbed. Obligations will extend throughout both that financial and real socio-economy and the specific natural functions of that financial sector will be condensed. When that financial system is considerably undercapitalised, it will not any more supply credit with regard to ordinary day to day business and the financial economy will suffer.

Based on the theoretical assumption that the projected value of the debt does not amend during the crisis, it can be demonstrated that

$$\mathbf{E}\hat{C}\check{s}\mathsf{F}_{i,t:t+T} = \Bbbk D_{i,t} - (1-\Bbbk)(1-LRSMES_{i,t:t+T})\mathbf{E}_{i,t} \qquad (3)$$

where $LRMSES$ (Long-Run Marginal Specific Expected Shortfall) is the expected the percentage of loss with regard to the firm's equity measured worth of value in the sequential event of the crisis. Aggregate NDSM Risk can be assumed of as the aggregate amount of the capital that the electoral government would have to render to bail out the economic financial system conditional basis on a financial distress. Note that in the estimation of aggregate NDSM Risk we ignore the firms that have specific capital superfluous or surplus (negative measured kind of capital shortfall). This is due to the reason that it is unlikely the capital will be straightforwardly mobilized all the way through mergers, private markets as well as loans during the time. It may also be much insightful to consider significantly the institution's major contribution to that financial system's specific capital shortfall. In the next sections this study discuss the NDSM Risk methodology demonstrated in this portion and apply it towards the Canadian banking sector and insurance based industries.

3. RESULTS

The undertaken variables and indicator information are as follows:

Variable 1: TD, Variable 2: Scotia Bank, Variable 3: BMO, Variable 4: RBC, Variable 5: CIBC
Indicator 1: Debt, Indicator 2: LRMSES, Indicator 3: Equity or Market Based Capitalization

The analysis of the Table yields following mentioned four observations. First, since the 2007 to 2009 financial worldwide crisis, NDSM Risk values of the topmost five Canadian banks demonstrated an overall decrease. Second, in FY2016 the systemic based risk values were comparatively uniformed crosswise all five banking sectors implying that overall institutions significantly would (approximately equally) contribute to the risk in the period of a financial crisis. Third, the systemic risk in the specific banking sector reached its five-year topmost maximum in the month of January 2016 which can be credited to the fact that the MSCI based World index (the specific market) was almost volatile, almost losing around *10%* during the first three number of weeks throughout the month. The main drivers at the back of the MSCI's specific decline were the decreasing price of oil as well as concerns regarding the China's economic significant slowdown. In addition, the Canadian firms were faced by means of increased volatility during the Canadian market as well as a weaker depreciated Canadian value of dollar. Fourth, the systemic risk with regard of Canadian banks remarkably increased throughout the last two fiscal years. To understand the reason of this increase this study decompose the sequential changes in NDSM Risk towards changes in the three indicators of debt, LRMSES, as well as market based capitalization.

Table 1: NDSM Risk Changes due to the changes in Debt, (million CAD) (2015M1-2016M06)

		V1	V2	V3	V4	V5	Total
Delta(Debt)	2014M12	2,799	1,004	54	1926	691	6473
	2015M12	8493	3318	6108	10742	2222	30883
	2015M12	(3613)	(1086)	(2837)	(4151)	(482)	(12168)
	2015M12	4791	1791	2766	3701	1309	14359
	2015M12	308	(531)	(2384)	(976)	33	(3210)
	2016M12	4842	4571	4178	9015	1148	23754
	2016M12	(3371)	(1712)	(1143)	(3617)	(52)	(9896)
SUMMATION		14250	7355	6742	16639	5210	50196

Table 2: NDSM Risk Changes due to the LRMSES, (million CAD) (2015M1 -2016M06)

		V1	V2	V3	V4	V5	Total
Delta(Risk)	2014M12	1839	923	(694)	376	1555	3999
	2015M12	(3052)	1928	(808)	2472	(708)	(169)
	2015M12	2660	(1997)	1277	(2433)	(74)	(566)
	2015M12	5939	4359	3053	4554	2963	20868
	2015M12	3546	3646	654	7057	1081	15985
	2016M12	(10752)	(639)	(2524)	(9241)	(2092)	(31006)
	2016M12	6735	155	193	3552	1894	13931
SUMMATION		6914	4019	1151	6337	4621	23042

Table 3: NDSM Risk changes due to the equity (million CAD) (2015M1-2016M06)

		V1	V2	V3	V4	V5	Total
Delta(Equity)	2014M12	(407)	2666	55	(241)	208	2279
	2015M12	1635	2728	3144	4005	2294	13805
	2015M12	1437	(810)	1043	(35)	(82)	1554
	2015M12	552	4863	648	2620	(1068)	7616
	2015M12	(2039)	2380	(2211)	(2370)	1216	(3024)
	2016M12	(2114)	(5936)	(374)	(72)	(1342)	(10538)
	2016M12	657	103	(1386)	(1614)	(22)	(2261)
SUMMATION		(280)	5993	918	1593	1206	9431

4. DISCUSSION

The analysis portrayed in demonstrates that individual should exercise the caution when using the NDSM Risk methodology. Although NDSM Risk is demonstrated as the positive expected significant capital shortfall, the issues raised here remarkably suggest that a somewhat diverse interpretation of the specific results should be undertaken when adopting this measure. On the one hand, the following significant facts make NDSM Risk a beneficial component of the systemic risk based analysis:

I. NDSM Risk was a significant measure of predictor in regard to the capital injections that is been carried out by the Fed in the timeline of 2007-2009 financial economic crisis.

II. NDSM Risk delivers beneficial rankings of systemically major risky firms. For instance, the NDSM Risk rankings already has determined Fannie Mae, Bear Stearns and Lehman Brothers, Freddie Mac, Morgan Stanley as top systemic significant contributors as in the early hours as Q1-FY2005.

III. Aggregate NDSM Risk provides early precautionary warning signals of the worsening macroeconomic contingency conditions. Brownlees and Engle (2016) portrayed that a raise in NDSM Risk predicted prospective declines in the industrial production as well as increases in the specific unemployment rate, as well as that the predictive remarkable ability of the aggregate NDSM Risk is much stronger during longer horizons.

IV. An important distinction between NDSM Risk and the majority of the market-based systemic risk indices could be demonstrated as this does not necessarily depend on the equity volatility as well as correlation, but it also unequivocally depends on the aggregate size and the total degree of leverage with regard to a financial firm.

On the other hand, considering the result as an example, the expected specific capital shortfall of the topmost five Canadian banks was around 80 billion CAD by the side of the end of 2008, or more than around 5% of Canadian GDP. This seems to be to some extent at odds with what was in point of fact observed during this crisis. Canadian financial based institutions did not necessitate bailout funds from the authority or government and on the whole, Canada accomplished outcome of result relatively well in the period of this timeline. However, there is still some argument about the overall strength of the Canadian overall banking system during the crisis in accordance with some disagreement that the Bank of Canada's liquidity kind of provision helped the sector evade any bailouts. Overall, there seems to be no authentic evidence suggesting that the NDSM Risk value of a given Canadian bank is identical to its expected capital specific shortfall. Perhaps, NDSM Risk for Canadian banks ought to be regarded as the tendency of a bank to suffer brutal losses during the crisis. Indeed, at the timeline of the 2007-2009 financial economic crisis, CIBC had high major values of NDSM Risk, whereas TD's NDSM Risk was significantly rather negligible. As it turned out, CIBC experienced vital outsized losses during this crisis, while TD's write-downs were particularly smaller.

5. CONCLUSION

Unavailability of data was unavoidable constraint of conducting this research. Policymakers should adopt diversified methodologies to take precautionary measure to recover or overcome this crises of distress. Early warning risk indicator adoption methodology should be selected as a preventive measure to safeguard during contingency moments. People should be made well aware of the negative consequences of this distress situation. Mass awareness initiatives as well as regulatory body should adopt prudential policy measure as an early warning system (EWS). Overall, the application measure of the NDSM Risk methodology to the Canadian banking specific sector reveals that opening from December 2015 the NDSM risk already has been remarkably increasing. For the analysed major insurance companies, only Manulife is particularly found to be systemically risky underneath this measure. Effective as well as efficient regulation having consideration of this type requires the identification focusing systemically important financial institutions (SIFIs). In this respect it is important to construct NDSM risk measures that properly identify SIFIs. Undoubtedly, NDSM risk measures are equally essential for the sake of investors who tend be aware in regard of the riskiness with respect to their investments. Although regulation as well as investment issues relevant to NDSM risk are significant for financial steadiness in any sovereign country, this is principally so for the Canada as the sovereign country has constantly topped the sequential list of the G7 countries with the foremost business environment as well as economic growth. Thus, a inaccuracy of calculation in regard to NDSM riskiness in Canada might have severe implications. Proper undertaking of this risk mitigation process could safeguard the sovereign economy to reasonable extent. Policymakers could adopt this methodology to protect from vulnerability with regard to undertake precautionary initiative.

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