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Interaction of Credit and Market Risks and Impact on Banks' Economic Capital

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ABSTRACT

Banks often measure the magnitudes of credit and market risks separately, and then add up the two to estimate economic capital. This approach ignores the complex interactions between the two risk types. We develop a model in which these risks are estimated jointly. We used both Value at Risk (VaR) and Conditional Value at Risk (CoVaR) risk measures to analyze the relation between market and credit risks interconnectedness among banks during financial stress. Our model is based on the market returns and total provisions in 37 banks in Asia, Europe, and North America. The results show that deliberately ignoring the interaction between these types of risk leads to either an under or overestimation of the sum of the magnitudes of the two risks, and hence, results in an over or underestimation of economic capital. It was concluded that during times of financial distress, an increase in a bank's provision would lead to an extreme loss in stock returns that were higher than the VaR value. This proves that underestimating credit risk can lead to an increase in the market risk faced by banks during financial distress.

INTRODUCTION

Successful risk management in a financial institution aims to both manage and measure risk to reach an optimal capital estimation that would serve the institution's risk appetite along with its business strategy. Typically, researchers model the risk distribution prior to measuring the level of risk.

Financial institutions are subject to two types of risk: credit and market risks. Distribution of each type of risk has a specific shape. Credit risk portfolios tend to generate right-skewed distributions because of occasional extreme losses, whereas market risk portfolios tend to generate left-skewed and fat-tailed distributions. Therefore, it is crucial to find an accurate way

to model different risk types to capture risk-specific properties such as, distribution tails, skewness, and kurtosis. We also capture the interdependence of these risks.

According to Bhattacharya and Thakor (1993), the modern theory of financial intermediation states that banks play two critical roles– 1. to transform the risk, and 2. to provide liquidity. Thus, liquidity and credit risk are closely linked. Breuer et al. (2010) argue that credit and market risks are also closely linked because the probability of default (PD) of clients depends on market prices such as exchange rates and interest rates. In addition, market losses depend on the signals sent to the market from changes in credit provisions.

Traditionally, if a portfolio is exposed to two or more imperfectly correlated risks, the sum of the capital needed to buffer against these risks should be higher than the amount of each risk alone. Breuer et al. (2010) show that, when assessing market and credit risks in trading and banking books, the risk of the total portfolio may be higher than the risk of each book independently. This may happen when the risks under consideration (market and credit risks) cannot be assessed separately. For some exposures to be accurately assessed, interactions of credit and market risks must be measured.

Few studies have investigated the interaction between credit and market risks in the banking sector in extreme situations. The 2008 financial crisis raised many concerns regarding how banks assess their risks. To address this issue, regulators such as the Basel Committee, Financial Supervisory Authority (FSA), and European Central Bank (ECB) issued several regulations on an accurate assessment of the economic capital to reflect the capital needed during times of distress. With the COVID-19 pandemic affecting the world now, assessing this risk interaction is becoming critical in bank survival. Kretzschmar et al. (2010) defined economic capital as the capital a financial institution needs to operate "as a solvent concern at a specified confidence level over a given time horizon."

Studying the interaction between different risk types raises an important question– what is the appropriate amount of economic capital needed once the interdependence between risks is accurately captured? This question is crucial for banks because it saves them from locking up large amounts of capital without putting it to any use. Moreover, capturing the interdependence between risks helps regulators have a better understanding of how to set capital requirements that would protect the banking sector from systemic failure.

There are many factors that affect market risk exposure and the credit risk probability of default. Therefore, the relationship between market and credit risks has different correlations, which can be negative or positive. Not having a model that explicitly incorporate this correlation during financial stress can lead to negative consequences on the bank survival. This study focuses on the effect of credit risk on market risk under extreme conditions to assess the impact of increasing or decreasing the growth rate of provisions on investors in the market. Our hypothesis is that during time of stress having extra provisions would lead to an extreme loss in market returns that are higher than the VaR value.

The remainder of this paper is structured as follows. Section 2 provides an overview of the existing literature. In Section 3, we present the data and methodology used to estimate the

integrated economic capital model derived from the interaction of market, credit, and liquidity risks. Section 4 presents the results. Finally, Section 5 concludes the paper.

LITERATURE REVIEW

Due to the evolution of financial markets and their rapid development, interest has been increasing in quantifying the risks facing financial institutions, through an integrated approach to risks to understand their interaction and interdependence. According to Bellini (2013), there are two well-known approaches to risk estimation that help integrate risks: top-down and bottom-up. Brodeur and Pergler (2010) state that the objective of the bottom-up approach is to ensure that all important risks are identified and prioritized to implement all the risk policies and processes required to control daily decision-making throughout an organization and have a robust risk culture. As against this, the top-down approach's objective is to have a clear insight into the top five to ten risks that affect an organization's performance to ensure that all management teams are well informed to be able to execute important decisions at the executive level. In addition, to keep the board of directors properly informed of the risk facing the institution.

Grundke (2010) showed that the top-down approach may lead to an underestimation of the total economic capital needed. In addition, the accuracy of the top-down approach depends on the copula used, strength and direction of the stochastic dependence among risk types, and the loss definition. On the other hand, Bellini (2013) followed the bottom-up approach to study banking solvency in the Italian economy in both the long and short run. The research studied a bank's ability to face interest rate, liquidity, and credit risks is linked to the shocks to macroeconomic variables that affect both its liabilities and assets. The study used data from 1990 to 2009. The macroeconomic data used were quarterly data including total free-on-board exports, gross domestic product, internal consumption, gross housing investments, unemployment rate, and added value of food, beverages, and tobacco. The study used data of 457 firms and banks on the return on assets, liquidity ratio, ratio of overall Italian credit available to a firm to the credit effectively used, and the ratio of debt to total assets. The research concluded that bank risk is associated with both assets and liabilities. Banks with perfectly matching liabilities and assets require lower economic capital and bear lower liquidity risks than banks that have positive maturity transformations between assets and liabilities, which subject them to higher risks in both the short and long run. Therefore, it is crucial for banks to assess their risk using an integrated approach, instead of assessing risks independently.

Some of the empirical literature available that focus on measuring credit risk interaction from market data includes, Kritzman et al. (2011), Lucas et al. (2014), Podlich and Wedow (2014), Betz et al. (2016), and Barigozzi and Brownlees (2019). While on the theoretical side, there is a growing literature including Freixas et al (2000), Peydró and Iyer (2005), Gai et al. (2011), Greenwood et al. (2015), Caballero and Simsek (2013), Duarte and Eisenbach (2015), Tian et al (2013), and Hale et al (2016), that analyze how balance sheet channels, such as loan syndication, interbank lending, or asset commonality induce interaction between market and credit risks and spread stress across banks.

Alessandri and Drehmann (2010) studied the interaction between credit and interest rate risks to estimate the required economic capital. They used Global Vector Autoregression, and the

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model was estimated for 1979Q1–2005Q4 for a bank in the UK. The model was based on accounting book values. The simulations show that the interaction between risks is crucial, and ignoring it leads to an overestimation of risk and a faulty estimation of the economic capital. Therefore, both regulators and risk managers should consider the interaction between different risk types because this interaction may lead to a higher capital level than the sum of the capital derived by measuring each risk independently. Drehmann et al. (2010) study the integration between credit and interest rate risks and its impact on economic capital by considering the repricing characteristics of liabilities, assets, and off-balance-sheet items. Their framework was illustrated by analyzing the impact of macroeconomic stress on a hypothetical but realistic bank. The simulation results show that the interaction between interest rate risk and credit risk is quantitatively significant and cannot be ignored. In conclusion, both studies highlight that importance of studying the interaction between risk to avoid the misallocation of capital utilized by banks.

Another study done by Breuer et al. (2010) assessed the interaction between market and credit risks in the context of foreign currency loans. They concluded that the separate estimation of market risk and credit risk may drastically underestimate the true risk and is a biased estimation of the economic capital. The example of a foreign currency loan portfolio is relevant because the exchange rate can be considered both a credit risk factor and a market risk factor. It is a credit risk factor because it affects the size of default losses and the PD. At the same time, it is a market risk factor because the exchange rate has an impact on portfolio value even if no defaults occur. In conclusion, market risk estimations must reflect the effects of credit risk events. Banks are not safe when they hold the sum of credit risk plus market risk capital. The authors suggest that regulators can ensure that a bank's economic capital is sufficient only if it considers the interaction between different types of risks.

Kretzschmar et al. (2010) implemented a dynamic economic scenario on the balance sheet of a European bank to calibrate the conditions that occurred at the end of 2007. They showed that using a correlation-based approach to calculate economic capital led to an undercapitalization of banks. They concluded that the use of a correlation matrix to capture the dependence between different asset class risks did not consider mutual dependencies driving the risk factors. Therefore, the integrated approach is more practical and realistic, and it estimates economic capital more accurately. Using the integrated approach rather than a correlation matrix allows a comparison based on risk-adjusted performance and provides a framework for an efficient stress testing (proper management of tail dependence).

In this study, we complement this literature by studying the effect of credit provisions in periods of distress when the increased provisions send a bad signal to the financial market. This bad signal will produce a decrease in stock prices, and hence, cause an extreme market loss to the bank. This is related to similar empirical papers of Tobias and Brunnermeier (2016) who proposed the CoVaR as a measure for systemic risk, which is the VaR of the risk understudy conditional on bank being under financial stress. They have concluded that during financial stress, the tail events tend to spill across other financial institutions. These spillovers are preceded by a "risk-buildup phase".

In conclusion, according to both Hartmann (2010) and Jarrow and Turnbull (2000), the interaction between market and credit risks is crucial and cannot be ignored. Because both risks are affected by the same economic factors, it is quite difficult to distinguish between the two risks in measurement and management. Even if certain factors associated with each risk can be separated, the two risks interact significantly in determining the asset values. Therefore, their interactions must be accounted for explicitly.

DATA AND METHODS

Data

To investigate the effects of credit and market risks and their interaction, we used a sample of 37 banks located in Asia, Europe, and North America. We used their monthly data from January 2000 to March 2021. Bank-level data were obtained from the Bloomberg database on market returns and total provisions.

Methods

The Value-at-Risk (VaR) is a widely used extreme risk measure in finance, particularly in risk management. Adrian and Brunnermeier (2011) first introduced Conditional Value-at-Risk (CoVaR) as a systematic risk measure to extend the VaR measure. This study uses both VaR and CoVaR risk measures to forecast systematic credit and market risks and applies them to the banking system. More precisely, we use the definition of CoVaR proposed by Adrian and Brunnermeier (2011) and extended by Girardi and Tolga Ergün (2013).

We define r_{it} as the return of bank i at time t, and let $\mathrm{VaR}_a(r_{it})$ be the VaR of r_{it} at a significance level $0 \leq \alpha \leq 1$. $\mathrm{VaR}_\alpha(r_{it})$ is defined as the a-quantile of the distribution of r_{it} given by

$$Pr[r_{it} \leq VaR_a(r_{it})] = \alpha. \quad (1)$$

Similarly, the CoVaR is defined as the VaR of bank i's return given that the credit provisions are below their VaR. Following Girardi and Tolga Ergün (2013)[1], we define the CoVaR risk measure $\mathrm{CoV}aR_{a,j3}(r_{it})$ as follows:

$$Pr[r_{it} \leq CoVaR_{a,j3}(r_{it}) | c_{it} \leq VaR_{j3}(c_{it})] = a. \quad (2)$$

where α and β are any given significance levels, and r_{mt} is the market return. Using this definition of the CoVaR, the CoVaR is, in fact, the VaR of r_{it} conditional on credit provisions c_{it} below its VaR. In this case, the CoVaR is seen as a measure of conditional downside risk. This captures the effect of credit conditions unfavorable to the bank's returns.

To compute the CoVaR parametrically, we use a copula to specify the joint distribution of r_{it} and c_{it}. Assume that (r_{it}, c_{it}) have copula C. Using Sklar's (1959) theorem, the joint cumulative distribution function (hereafter CDF) is given by

[1] For more information on systemic risk and CoVaR see Mainik and Schaanning (2014) and Puzanova and Dullmann (2013) among others.

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$$P\,r\,(r_{it} \leq\ r_i, c_{it}\ \leq\ r_m) =\ C(u_{it}, u_{it}), \quad (3)$$

where $u_{it} = F_{rit}\,(r_i)$ and $v_{it}\ =\ F_{cit}\,(c_i)$, and F_{rit} and F_{cit} are the CDFs for r_{it} and c_{it}, respectively. It follows that the conditional distribution of the return to be below a certain level r conditional on the provisions is below a given level c and is given by

$$P\,r\,(r_{it} \leq\ r \mid c_{it}\ \leq\ \ c) = \frac{C\,(u_{it}, v_{it})}{v_{it}}$$

Equation (2) can be rewritten as

$$\frac{C\,\left(\beta, F_{r_{IT}}\left[\,CoVaR_{a,\beta}\,(v_{it})\right]\right)}{\beta} =\ \alpha$$

or equivalently as,

$$C\left(\beta, F_{r_{it}}\ \left[CoVaR_{a,\beta}(r_{it})\right]\right) = \alpha\beta. \quad (4)$$

Moreover, assume that C is an Archimedean copula with a generator ψ, that is,

$$C\left(v_{it}\ , v_{it}\right) = \psi^{-1}[\,\psi(v_{it}) +\ \psi(v_{it})].$$

Therefore, we have

$$CoVaR_{a,\beta}\,(v_{it}) = f_{r_{it}}^{-1}\,[\psi^{-1}\,(\alpha\beta) -\ \psi(\alpha))].$$

MODEL SPECIFICATION

The Marginal Distribution

To model the marginal distributions, we use Hansen's (1994) skewed t-distribution. This skewed t-distribution has a general form density function as follows:

$$f(x_{t+1}\,) = \begin{cases} \frac{bc}{\sigma_t}\,(1 + \frac{1}{v-2}(\frac{b\,(x_t+1-\mu_{t)+\alpha\sigma_t}}{(1-\lambda)\sigma_t})^2) & if\ x_{t+1}\ <\ \mu_t - \frac{a}{b}\,\sigma_t \\ \frac{bc}{\sigma_t}(1 + \frac{1}{v-2}(\frac{b\,(x_t+1-\mu_{t)+\alpha\sigma_t}}{(1-\lambda)\sigma_t})^2) & Otherwise \end{cases} \quad (5).$$

where x is a real random variable ($x\ =\ r_{it}$), v is the shape parameter ($2 < v < \infty$), the parameter λ denotes the asymmetry of the distribution ($-1\ <\lambda\ <\ 1$), μ_t , and σ_t^2 are the conditional mode and conditional scale of the return, respectively.

$$a = 4\,\lambda c\,\frac{v-2}{v-2}$$
$$b^2 = 1 + 3\lambda^2 + a^2$$

and

$$c = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi\,(v-2)}\,\Gamma\left(\frac{v}{2}\right)}$$

The function r(x) is a Gamma function given by

$$\Gamma(x) = \int_0^{+\infty} t^{x-1} \exp[-t]\, dt,$$

The skewed t-distribution reduces to a t-distribution when $\lambda = 0$. Oh, and Patton (2013) used the skewed t-distribution in financial econometrics.

The CDF and the quantile of (6) are given by:

$$f(r_{t+1}) = \begin{cases} (1-\lambda)\, T\left(\dfrac{b\,(r_t + 1 - \mu_t) + \alpha\sigma_t}{(1-\lambda)\sigma_t}, v\right) & if\ r_{t+1} < \mu_t - \dfrac{a}{b}\,\sigma_t \\ (1-\lambda)\, T\left(\dfrac{b\,(x_t + 1 - \mu_t) + \alpha\sigma_t}{(1-\lambda)\sigma_t}, v\right) - \lambda) & Otherwise \end{cases}$$

and

$$q_t = \begin{cases} \mu_t + \sigma_t\, T^{inv}\left(\dfrac{u}{1-\lambda}, v\right) if\ u < 1-\lambda \\ \mu_t + \sigma_t\, T^{inv}\left(\dfrac{u+\lambda}{1+\lambda}, v\right)\ Otherwise \end{cases}$$

where the function $T^{inv}(.,v)$ is the quantile of the standard Student's t-distribution.

Specification Of the Marginal First and Second Moments

We use an Autoregressive Moving Average Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) model to allow time-varying conditional location and scale parameters. We used the following ARMA (1,1) model for the location parameter μ_t

$$xt = \mu_t + \varepsilon_t,$$

where x is the return r_i at time t and

$$\mu_t = \mu + \phi r t_1 + \varepsilon_{t-1}, \qquad (7)$$

The conditional scale parameter σ_t^2is modeled as Nelson's (1991) exponential GARCH model that is, EGARCH (1,1) given by

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$$In\left(\sigma_{i,t}^2\right) = \sigma_i + \alpha_i \frac{|\varepsilon_t - 1|}{\sigma_{i,t-1}} + \delta i \frac{\varepsilon_{t-1}}{\sigma_{i,t-1}} + \beta_i In\left(\sigma_{i,t-1}^2\right). \quad (8)$$

Parameters α_i, δ_i, and β_i capture the news effect, volatility persistence, and asymmetrical effect, respectively. Thus, if $\delta_i < 0$, bad news ($\varepsilon_{t-1} < 0$) has a greater effect on volatility than good news ($\varepsilon_{t-1} > 0$) does. Note that because the distribution of ε_t is asymmetric, μ_t is the conditional mode rather than the conditional mean. However, the skewed t-distribution reduces to the t-distribution when $\lambda = 0$ and μ_t becomes the conditional mode and conditional mean at the same time, owing to the symmetry of the distribution in this case.

Specification of Dependence model

To model the dependence between the variables of interest, we use the Clayton copula. The copula CDF is given by:

$$c(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{-\frac{1}{\theta}}$$

Clayton copula is a member of the Archimedean copula family. It has a dependence parameter

$\theta \in (-1, +\infty)$ and generator function $\psi(u) = \frac{u^{-\theta}-1}{\theta}$. Perfect dependence is reached at $\theta \longrightarrow +\infty$, whereas independence is attained at $\theta = 0$.[2]

Recall that we defined the CoVaR for the Archimedean copula as

$$CoVaR_{a,\beta,t}(Y_t) = [\psi^{-1}(\psi(\alpha\beta) - \psi(\alpha))], \quad (9)$$

and the quantile of the marginal Skewed t-distribution as

$$q_t = \begin{cases} \mu_t + \sigma_t T^{inv}\left(\frac{u}{1-\lambda}, v\right) if\ u < 1-\lambda \\ \mu_t + \sigma_t T^{inv}\left(\frac{u+\lambda}{1+\lambda}, v\right)\ Otherwise \end{cases}$$

It follows, therefore, that the VaR and CoVaR are given by

$$VaR_a(\mathcal{X}_t) = \begin{cases} \mu_t + \sigma_t T^{inv}\left(\frac{a}{1-\lambda}, v\right) if\ a < 1-\lambda \\ \mu_t + \sigma_t T^{inv}\left(\frac{a+\lambda}{1+\lambda}, v\right)\ Otherwise \end{cases}$$

and

[2] For further details on copula see Rodriguez (2007), Joe (1997), Joe and Xu (1996), and Sklar (1959).

$$\mathrm{Co}VaR_{a,\beta}(\mathcal{X}_t) = \begin{cases} \mu_t + \sigma_t\, T^{inv}\left(\frac{(a\beta)^{-\theta} - a^{-\theta} + 1)^{-\frac{1}{\theta}}}{1-\lambda}, v\right) if\ ((a\beta)^{-\theta} - a^{-\theta} + 1)^{-\frac{1}{\theta}} < 1-\lambda \\ \mu_t + \sigma_t\, T^{inv}\left(\frac{(a\beta)^{-\theta} - a^{-\theta} + 1)^{-\frac{1}{\theta}+\lambda}}{1-\lambda}, v\right) \qquad Otherwise \end{cases} \quad (10)$$

The systematic extreme risk is given by the difference between the CoVaR and VaR over the VaR:

$$Sys_{a,\beta}\,(x_t) = \frac{CoVaR_{a,\beta}\,(x_t) \text{ — } VaR_a(x_t)}{VaR_a(x_t)} \times 100.$$

where $x_t = r_{it}$. For example, in the case of returns $(x_t = r_{it}), Sys_{a,\beta}\,(x_t) > 0$ implies that given that the provisions losses are higher than their VaR, the extreme market losses will be even higher when $Sys_{a,\beta}\,(x_t) < 0$.

RESULTS AND DISCUSSION

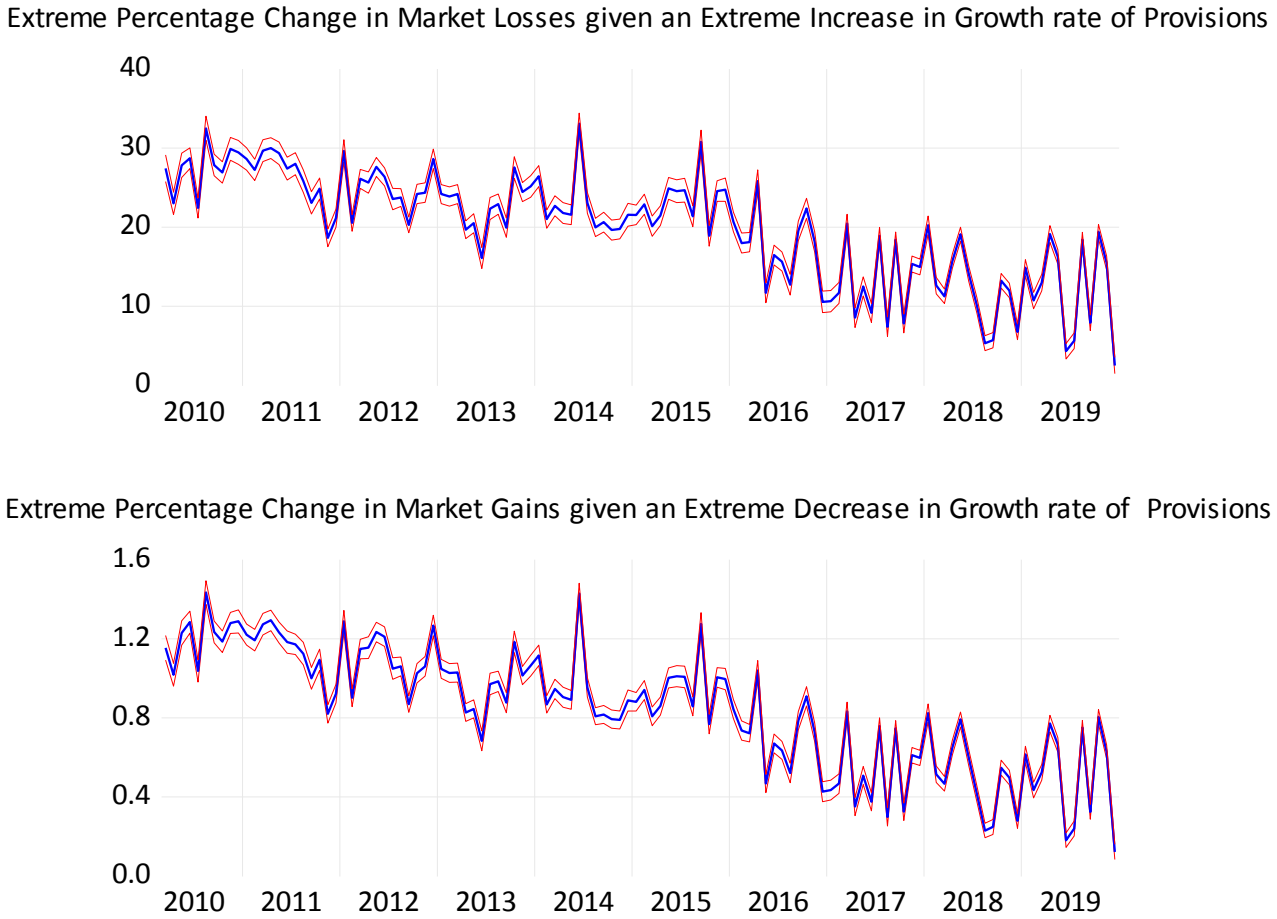
Table 1: Descriptive Statistics

	Extreme Returns Loss Conditional on Extreme provisions Growth rate Increase		Extreme Returns Gain Extreme Returns' Loss Conditional on Extreme provisions Growth rate Decrease	
Bank Name	Mean	Std. Dev.	Mean	Std. Dev.
DBS Group Holdings Ltd (SGX: D05)	53.94	18.88	1.87	0.61
BNP Paribas SA (ENXTPA : BNP)	8.04	8.88	0.31	0.34
HSBC Holdings plc (LSE: HSBA)	37.67	9.07	1.68	0.47
Banco Santander, S.A. (BME:SAN)	36.99	10.46	1.66	0.58
Société Générale Société anonyme (ENXTPA : GLE)	-0.04	14.77	0.05	0.58
Lloyds Banking Group plc (LSE: LLOY)	-18.29	11.52	-0.65	0.40
ING Bank N.V.	12.09	31.30	0.39	1.11
ING Groep N.V. (ENXTAM: INGA)	20.06	13.75	0.82	0.63
Banco Bilbao Vizcaya Argentaria, S.A. (BME:BBVA)	30.53	14.94	1.51	0.76
Standard Chartered PLC (LSE: STAN)	36.30	13.44	1.60	0.69
JPMorgan Chase & Co. (NYSE: JPM)	-8.93	13.04	-0.30	0.45
JPMorgan Chase Bank, National Association (BDL:166810345)	-8.93	13.04	-0.30	0.45
Bank of America Corporation (NYSE: BAC)	7.40	7.27	0.29	0.29
Citigroup Inc. (NYSE:C)	12.56	12.16	0.51	0.51
Bank of America, National Association	7.40	7.27	0.29	0.29
Wells Fargo & Company (NYSE: WFC)	9.51	15.47	0.38	0.61
Wells Fargo Bank, National Association	9.51	15.47	0.38	0.61
The Toronto-Dominion Bank (TSX:TD)	26.96	4.31	1.18	0.23
Royal Bank of Canada (TSX: RY)	17.49	5.36	0.70	0.24

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The Bank of Nova Scotia (TSX: BNS)	-3.53	7.94	-0.13	0.30
Bank of Montreal (TSX: BMO)	22.65	9.12	1.01	0.47
Canadian Imperial Bank of Commerce (TSX:CM)	36.07	5.55	1.72	0.33
U.S. Bancorp (NYSE: USB)	-0.62	10.16	-0.02	0.36
U.S. Bank National Association	-0.62	10.16	-0.02	0.36
Truist Financial Corporation (NYSE: TFC)	36.06	10.58	1.42	0.47
The PNC Financial Services Group, Inc. (NYSE: PNC)	15.13	8.83	0.66	0.43
PNC Bank, National Association	15.13	8.83	0.66	0.43
TD Bank, N.A.	47.85	11.92	1.96	0.39
The Bank of New York Mellon	21.75	9.93	1.00	0.55
Capital One, National Association	83.75	37.81	2.80	1.21
National Bank of Canada (TSX:NA)	12.22	5.19	0.50	0.23
Fifth Third Bancorp (NasdaqGS:FITB)	23.86	11.24	0.96	0.51
HSBC USA Inc.	51.27	18.67	2.08	0.83
KeyCorp (NYSE:KEY)	29.03	8.78	1.27	0.46
The Northern Trust Company	34.55	3.86	1.93	0.43
Regions Financial Corporation (NYSE: RF)	24.32	9.46	0.98	0.42
M&T Bank Corporation (NYSE: MTB)	5.00	16.21	0.18	0.60

Graph 1:



Note: The red lines represent a 95% confidence interval.

As presented in Table 1 and Graph 1, our results show that increasing the provisions during times of financial distress signals to investors a problem with the bank, which is reflected in the loss of stock returns. These are extreme losses in market returns that are higher than the VaR value. To the contrary, under normal conditions, if banks decrease their provision levels, this does not result in a significant gain in stock returns. In other words, the decreasing growth rate of provisions does not signal to investors a bank's better financial health. This implies that underestimating the effect of credit risk during times of distress may induce extreme market losses because investors are risk averse and prefer to invest in banks with a cushion against the credit risk to protect their investments.

CONCLUSION

The lack of studies that combine the effects of credit and market risks and the effect of interaction between them motivated us to investigate this topic within. Credit and market risks are considered reciprocal risks and are recognized as the main determinants of bank economic capital. Our empirical approach is based on VaR and CoVaR measures of extreme risk. The empirical analysis in this study shows the effect of credit risk on market risk in the extreme situation.

The empirical results indicate that the decreasing growth rate of provisions does not signal to investors that a bank is in a better financial condition than that when its growth rate of

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provisions increases. However, during times of distress, the growth rate of provisions significantly impacts market stock prices. This indicates that underestimating credit risk may lead to severe market losses, which may, in turn, impact a bank's economic capital. This is consistent with Tobias and Brunnermeier (2016) who proposed the CoVaR as a measure for systemic risk and concluded that during financial stress, the tail events tend to spill across other financial institutions. These spillovers are preceded by a "risk-buildup phase". Our model captures this "risk-buildup phase" during times of stress that can impact the entire market if more than one financial institution falls. Moreover, we show that market information-based measures of interdependence (reflected in market returns) can serve well as risk monitoring tools in the absence of disaggregated high- frequency bank fundamental data. For future enhancements, our model can be replicated using high frequency data that reflect the banks fundamental information (at the best are available annually or quarterly on their financial statements).

References

Adrian, T. and Brunnermeier, M. (2011), CoVaR (No. w17454), National Bureau of Economic Research.

Alessandri, P. and Drehmann, M. (2010). An economic capital model integrating credit and interest rate risk in the banking book. Journal of Banking & Finance, 34(4), 730–742. https://doi.org/10.1016/j.jbankfin.2009.06.012

Barigozzi, M., & Brownlees, C. (2019). Nets: Network estimation for time series. Journal of Applied Econometrics , 34(3), 347-364.

Bellini, T. (2013). Integrated bank risk modeling: A bottom-up statistical framework. European Journal of Operational Research, 230(2), 385–398. https://doi.org/10.1016/j.ejor.2013.04.03

Betz, F., Hautsch, N., Peltonen, T. A., & Schienle, M. (2016). Systemic risk spillovers in the European banking and s overeign network. Journal of Financial Stability, 25, 206-224.

Bhattacharya, S. and Thakor, A. (1993). Contemporary banking theory. Journal of Financial Intermediation, 3(1), 2–50. https://doi.org/10.1006/jfin.1993.1001 Bloomberg. Terminal. Bloomberg 2021.

Breuer, T., Jandačka, M., Rheinberger, K., and Summer, M. (2010). Does adding up of economic capital for market- and credit risk amount to conservative risk assessment? Journal of Banking & Finance, 34(4), 703–712. https://doi.org/10.1016/j.jbankfin.2009.03.013

Brodeur, A., & Pergler, M. (2010). Top-down ERM: a pragmatic approach to managing risk from the C-suite. McKinsey Working Papers on Risk, Paper 22, McKinsey & Company, Washington, DC, USA.

Caballero, R. J., & Simsek, A. (2013). Fire sales in a model of complexity. The Journal of Finance, 68(6), 2549-2587 .

Duarte, F., & Eisenbach, T. M. (2015). Fire-sale spillovers and systemic risk. Staff Report no. 645.

Drehmann, M., Sorensen, S., and Stringa, M. (2010). The integrated impact of credit and interest rate risk on banks: A dynamic framework and stress testing application. Journal of Banking & Finance, 34(4), 713–729. https://doi.org/10.1016/j.jbankfin.2009.06.009

Freixas, X., Laeven, L., & Peydró, J. L. (2015). Systemic risk, crises and macroprudential policy.

Gai, P., Haldane, A., & Kapadia, S. (2011). Complexity, concentration, and contagion. Journal of Monetary Economi cs, 58(5), 453-470.

Girardi, G. and Tolga Ergün, A. (2013). Systemic risk measurement: Multivariate GARCH estimation of CoVaR. Journal of Banking & Finance, 37(8), 3169–3180. https://doi.org/10.1016/j.jbankfin.2013.02.027

Greenwood, R., Landier, A., & Thesmar, D. (2015). Vulnerable banks. Journal of Financial Economics, 115(3), 471-485.

Grundke, P. (2010). Top-down approaches for integrated risk management: How accurate are they? European Journal of Operational Research, 203(3), 662–672. https://doi.org/10.1016/j.ejor.2009.09.015

Hale, G., Kapan, T., & Minoiu, C. (2016, February). Crisis transmission through the global banking network. San Fr ancisco, CA, USA: Federal Reserve Bank of San Francisco.

Hansen, B. (1994). Autoregressive conditional density estimation. International Economic Review, 35(3), 705–730. https://www.jstor.org/stable/2527081

Hartmann, P. (2010). Interaction of market and credit risk. Journal of Banking & Finance, 34(4), 697–702. https://doi.org/10.1016/j.jbankfin.2009.10.013

Jarrow, R. and Turnbull, S. (2000). The intersection of market and credit risk. Journal of Banking & Finance, 24(1–2), 271–299. https://doi.org/10.1016/s0378-4266(99)00060-6

Joe, H., (1997), Multivariate Models and Multivariate Dependence Concepts. London: Chapman and Hall. http://dx.doi.org/10.1201/b13150

Joe, H., and Xu, J.J., (1996), The estimation method of inference functions for margins for multivariate models, Technical Report 166, Department of Statistics, University of British Columbia. https://doi.org/10.14288/1.0225985

Kritzman, M., Li, Y., Page, S., & Rigobon, R. (2011). Principal components as a measure of systemic risk. The Journ al of Portfolio Management, 37(4), 112-126.

Kretzschmar, G., McNeil, A., and Kirchner, A. (2010). Integrated models of capital adequacy– Why banks are undercapitalised. Journal of Banking & Finance, 34(12), 2838–2850. https://doi.org/10.1016/j.jbankfin.2010.02.028

Lucas, A., Schwaab, B., & Zhang, X. (2014). Conditional euro area sovereign default risk. Journal of Business & Eco nomic Statistics, 32(2), 271-284.

Mainik, G. and Schaanning, E. (2014). On dependence consistency of CoVaR and some other systemic risk measures. Statistics & Risk Modeling, 31(1), 49–77. https://doi.org/10.1515/strm-2013-1164

Nelson, D. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347–370. https://www.jstor.org/stable/2938260

Oh, D. and Patton, A. (2013). Simulated method of moments estimation for copula-based multivariate models. Journal of the American Statistical Association, 108(502), 689–700. https://doi.org/10.1080/01621459.2013.785952

Podlich, N., & Wedow, M. (2014). Crossborder financial contagion to Germany: How important are OTC dealers? I nternational Review of Financial Analysis, 33, 1-9.

Peydró, J. L., & Iyer, R. (2005). How Does a Shock Propagate? A Model of Contagion in the Interbank Market Due t o Financial Linkages. A Model of Contagion in the Interbank Market Due to Financial Linkages (May 2005).

Puzanova, N. and Düllmann, K. (2013). Systemic risk contributions: A credit portfolio approach. Journal of Banking & Finance, 37(4), 1243–1257. https://doi.org/10.1016/j.jbankfin.2012.11.017

Rodriguez, J. (2007). Measuring financial contagion: A copula approach. Journal of Empirical Finance, 14(3), 401–423. https://doi.org/10.1016/j.jempfin.2006.07.002

Tian, S., Yang, Y., & Zhang, G. (2013). Bank capital, interbank contagion, and bailout policy. Journal of Banking & F inance, 37(8), 2765-2778.

Tobias, A., and Brunnermeier, M. K. (2016). CoVaR. The American Economic Review, 106(7), 1705.

Sklar, A. (1959). Fonctions de répartition à n dimensions et leurs marges. Publications de l'Institut Statistique de l'Université de Paris, 8, 229–231.