MARKET AND CREDIT RISK ANALYSIS OF HSBC BANKING GROUP

Abstract

This essay will first examine the market risk of HSBC Banking Group using a Parametric Value-at-Risk approach. Using historical daily returns from 2014 to 2019, assuming this period was free of major shocks, a benchmark comparison with its industry peers was done. Results show that HSBC exhibits lower market risk than its major competitors in the industry. The essay will then examine the firm-level determinants of credit risk for HSBC Banking Group while also analysing the effect of these determinants on the bank's credit risk during the Covid-19 pandemic.

1. Market Risk Analysis of HSBC Banking Group

1.1. Introduction

Market risk refers to the potential loss of earnings that a financial institution may face due to unforeseen fluctuations in security prices or market rates. This risk is a primary concern for financial institutions, especially banks, as a significant portion of their assets comprises trading portfolios. To increase their non-interest income, banks have diversified from their traditional revenue stream (Duho, Onumah and Owodo, 2019) of interest spread to maintaining active trading portfolios, changing the nature of significant banks to an investment-oriented bank. Köhler (2014) and Lee, Yang and Chang (2014) argue that non-interest income is highly volatile and investment-oriented banks. When they increase their share of non-interest income, their risk significantly increases compared to smaller retail banks. As such, their exposure to market risk cannot be downplayed.

Value at risk (VaR) is the maximum potential loss in a worst-case scenario that could occur during a predetermined time horizon with a certain probability, assuming a normal market condition free from significant disruptions. Parametric VaR is a commonly used method to calculate the VaR. It involves using a given data set's mean and standard deviation to calculate the VaR. This method also assumes that the data follows a normal distribution, an essential assumption to consider while using this method. The Monte Carlo simulation approach will overcome the barrier of limited observations that can be obtained. However, with enough sample size, the VaR obtained from the simulation will converge into that of parametric VaR as it takes on the distribution of the original data. As enough data was used to create the sample while calculating the VaR, the Monte Carlo simulation was not performed for this analysis.

Table 1: Descriptive Statistics for Bank Stock Returns

	Santander	*NatWest*	*Lloyds*	*Barclays*	*HSBC*
Mean	-0.009%	-0.016%	-0.004%	-0.016%	0.017%
Standard Deviation	1.879%	1.955%	1.640%	1.831%	1.207%
Kurtosis	4.963	12.463	34.103	17.174	3.103
Skewness	-0.596	-0.878	-1.431	-1.420	-0.118
Minimum	-16.084%	-19.899%	-23.570%	-19.454%	-6.766%
Maximum	7.320%	10.852%	12.724%	7.881%	6.452%
Samples	1,515				

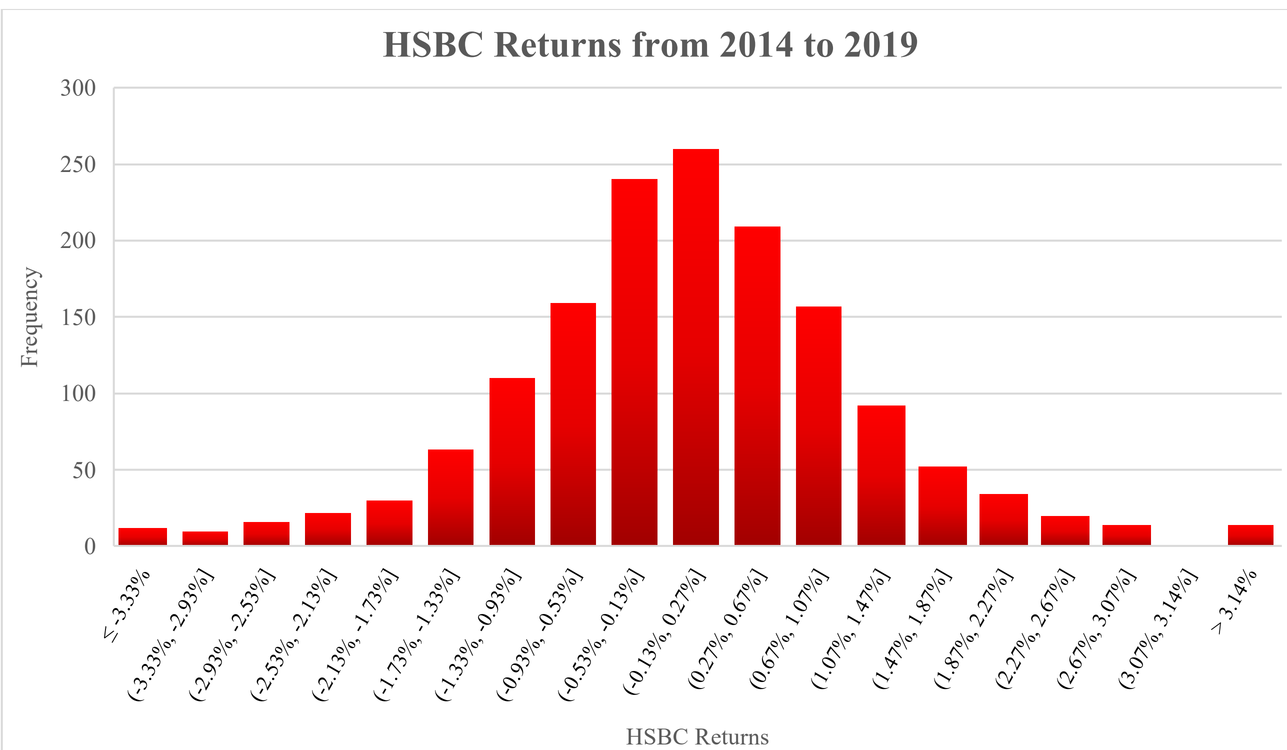

Figure 1: Histogram of HSBC Returns from 2014 to 2019

1.2. Calculating the VaR

The daily returns for the peer group (Banco Santander, NatWest, Lloyds and Barclays) and subject (HSBC) banks over six years (2014-2019) were first calculated for the benchmark analysis. The six-year period was relatively shock-free compared to the global crises on either side of the decade. Then, the mean and standard deviation were calculated for each of the bank stocks, and these were taken as the parameters to calculate the VaR (Table 1). Using a 5% significance level, the *z-value* of ***1.645*** was then calculated. This can also be altered to check the VaR at other confidence levels if required. As VaR is a left-tail check, I have used the following formula to calculate the estimated daily VaR level:

$$Daily\ Value\ at\ Risk\ = -\alpha \times \sigma + \mu$$

$where,$

$\alpha = z - value\ at\ predetermined\ confidence\ level$

$\sigma = Standard\ deviation\ of\ the\ daily\ returns$ $\quad$ $\mu = Mean\ of\ the\ daily\ returns$

However, as the parameters were calculated using the daily returns, the formula above only gives us the daily VaR level. To annualise the VaR level to state it as an annual parametric VaR, the following conversion is performed:

$$Annual\ Value\ at\ Risk\ = -\alpha \times \sigma \times \sqrt{t} + \mu \times t$$

$where,$

$\alpha = z - value\ at\ predetermined\ confidence\ level$ $\quad$ $t =\ annual\ trading\ days$

$\sigma = Standard\ deviation\ of\ the\ daily\ returns$ $\quad$ $\mu = Mean\ of\ the\ daily\ returns$

The daily VaR and the annual VaR at a 5% significance level are summarised in Table 2.

Table 2: Daily and Annual VaR for peer group and subject banks

	Bank	**Daily VaR**	**Annual VaR**
Peer Group	Banco Santander	-3.10%	-51.01%
	NatWest	-3.23%	-54.82%
	Lloyds	-2.70%	-43.59%
	Barclays	-3.03%	-51.72%
Subject	HSBC	-1.97%	-27.21%

The benchmark annual VaR for the peer group was then calculated on a weighted average basis, with each bank's weight being a proportion of their market capitalisation to total market capitalisation of the peer-group banks, measured on 31 December 2019 (Table 3). As a general trend at the individual bank level, it can also be observed that as the size (measured by market capitalisation) increased, that led to an increase in the VaR level

Table 3: Weighted Average VaR calculation as a benchmark

Peer Group Banks	***Market Capitalisation (£m)***	***Annual VaR***	***Weighted Average VaR***
Banco Santander	93,490	-51.01%	-17.21%
Natwest	51,325	-54.82%	-10.15%
Lloyds	77,338	-43.59%	-12.16%
Barclays	54,963	-51.72%	-10.26%
Total	**277,117**		**-49.78%**

Table 4: Value-at-Risk Summary for Benchmark Comparison for £10 million portfolio

	Benchmark	***HSBC***
Value-at-Risk level	49.78%	27.21%
Value-at-Risk amount (£millions)	4,978,343	2,721,201

Findings summarised in Table 4 indicate that the HSBC stock seems less susceptible to fluctuations in the overall market under normal circumstances as HSBC's annual parametric VaR at a 5% significance level is considerably lower than the computed benchmark value comprised of its peer groups. For a £10 million investment, it is estimated that there is a 95% probability that the average losses for similar banks to HSBC will not incur a loss of more than £4.98 million over a year (or a 5% possibility that these losses could be more than £4.98 million over a year), while there is a 95% probability that HSBC will not lose more than £2.7 million over a year (or a 5% possibility that these losses will exceed £2.7 million over a year). This implies that investing in HSBC common stocks will help minimise the overall VaR of the portfolio, potentially improving the overall VaR of the fund and increasing overall returns.

However, as aforementioned, using the parametric method to compute VaR assumes a normal distribution and is, thus, unsuitable when data indicates non-normality, such as asymmetry or leptokurtosis. When non-normalities in parametric VaR are identified, it may be better to use a non-parametric method to compute VaR as it can capture the outliers due to its more straightforward approach to computation and will ensure a robust risk assessment. Lechner and Ovaert (2010) suggest that no specific method is superior to other methods as they all have their shortcoming and benefits. Ultimately, the choice of the VaR method depends upon the characteristics of data and portfolio risk management needs.

2. The measures and determinants of credit risks of HSBC Banking Group during the COVID-19 pandemic

Credit risk refers to the possibility of a bank being unable to recover the promised cash flows on its financial entitlements. Given the nature of banking, which heavily relies on lending, credit risk is a significant risk that plays an essential role in a bank's survival (Giesecke, 2004). This risk can arise from idiosyncratic factors, such as lending to a particular customer, or systematic factors that affect the entire economy. While the former can be identified and potentially moderated through diversification of the loan portfolio and effective credit policies, the latter must be mitigated through anticipation and preparedness from the bank to face challenges head-on. Examples of exacerbated systematic risks include the Global Financial Crisis of 2008 (GFC 2008) and the COVID-19 pandemic. Evaluating the creditworthiness of borrowers has become more complex during and after the COVID-19 pandemic due to the unusual nature of the crisis. This essay will discuss how banks measure credit risk and the factors that determine credit risk, particularly during the recent COVID-19 pandemic.

GFC 2008 postulated the Basel Committee to recognise the shortcomings of Basel-II and develop more comprehensive rules and guidelines for the capital adequacy framework for the banks to follow, which ultimately aimed to curtail the total bank risk and, thereby, the credit risk. Samad (2012) identified specific credit risk measurement ratios as more significant than others in that they can predict the risk of bank failures. Salas and Saurina (2002) and Samad (2012) concluded that NPLs were the prime reason for bank failures. It is necessary to note that NPLs are not just a standalone item but a culmination of different macroeconomic and bank-specific factors such as inflation, bank management and the business cycle (Tehulu and Olana, 2014; Dimitrios, Helen and Mike, 2016; Naili and Lahrichi, 2022). Based on these previous studies, we can identify a few bank-specific factors to measure HSBC UK's credit risk under normal market conditions and during crises.

(i) Bank Size: It is widely debated whether a bank's size impacts its NPLs. Some experts argue that larger banks have better risk management and diversification strategies, which could lead to fewer NPLs (Salas and Saurina, 2002). However, others believe that larger banks may take on riskier lending practices due to the perception that they are "too big to fail," potentially increasing the number of NPLs (Haq and Heaney, 2012; Louzis, Vouldis and Metaxas, 2012). The research results on this topic are mixed, with some studies showing a negative relationship between bank size and NPLs while others find a positive one. Diverging from these views, Boudriga, Boulila Taktak and Jellouli (2010) find no significant relationship between bank size on credit risk.

(ii) Profitability Ratios (ROA and ROE): Several studies have explored the correlation between banks' performance and NPLs. The focus has been on whether profitability, as a performance indicator, affects the levels of NPLs. Experts argue that profitable banks, with a stronger desire for growth and the ability to handle unexpected events, have fewer NPLs (Radivojevic and Jovovic, 2017; Lafuente, Vaillant and Vendrell-Herrero, 2019a). On the other end, Louzis, Vouldis and Metaxas (2012) suggest that less profitable banks take on more risk to compensate for losses caused by management inefficiencies, thereby increasing NPLs. Similarly, Rajan (1994) argues profitable banks might engage in unethical earnings while approving bad loans for short-term gain, which could increase NPLs in the long run.

(iii) Capital Adequacy Ratio (CAR): The impact of the capital adequacy ratio on the credit risk of banks has been an ongoing debate. Salas and Saurina (2002) and Berger and DeYoung (1997) argue that a low capital ratio might encourage risky behaviour by managers since they have less to lose in the event of default. Boudriga, Boulila Taktak and Jellouli (2010) and (Ghosh, 2017) however find contradicting evidence, suggesting that banks with higher capital ratios will take on more risk as they are not bound by regulatory pressures to lower credit risk as they have a high capital cushion to absorb losses.

(iv) Credit growth: Credit growth is one of the key determinants of credit risk. Studies have found a positive relationship between credit growth and risk suggesting that rapid lending to meet targets may lead to riskier lending and defaults as screening resources are overwhelmed (Naili and Lahrichi, 2022) and loan quality decreases (Salas and Saurina, 2002). On the contrary, Boudriga, Boulila Taktak and Jellouli (2010) in their investigation of banks in the MENA region (Middle East and North Africa) find that lending-focused banks prioritising risk management tend to have superior credit assessment effectiveness.

(v) Operating efficiency: There are different views on the relationship between operating efficiency and NPLs. Studies suggest a few internal and external factors are at play for this negative relationship. Louzis, Vouldis and Metaxas (2012) conclude that management incompetency can foster inefficiency and poorly managed banks are likelier to make bad loans, leading to more NPLs. Furthermore, they also suggest that some banks, although they might be efficient in the short-run by cutting back on loan screening and monitoring costs in the short-run, this myopic vision for efficiency can result in higher NPLs in the long run.. Berger and DeYoung (1997) suggest that unexpected economic slowdowns and downturns can lead to increased NPLs, making banks less efficient.

Building on studies by Salas and Saurina (2002), Ghosh (2017) and Naili and Lahrichi (2022), we can develop our dependent variable as ***Credit Risk***. Similarly, based on the previous literature, our independent variables will be ***Bank Size*** (Salas and Saurina, 2002; Louzis, Vouldis and Metaxas, 2012) *,* ***ROA*** (Louzis, Vouldis and Metaxas, 2012; Radivojevic and Jovovic, 2017), ***ROE*** (Louzis, Vouldis and Metaxas, 2012; Radivojevic and Jovovic, 2017; Naili and Lahrichi, 2022), ***CAR*** (Ghosh, 2017; Radivojevic and Jovovic, 2017; Naili and Lahrichi, 2022)*,* ***Credit Growth*** (Salas and Saurina, 2002; Naili and Lahrichi, 2022)*,* ***Operating Efficiency*** (Louzis, Vouldis and Metaxas, 2012; Ghosh, 2017; Naili and Lahrichi, 2022) and *COVID-19 Crisis* as a binary variable taking value of 1 during the period of the crisis, a baseline regression model is developed:

$$Credit\ Risk = \beta_0 + \beta_1\ Bank\ Size + \beta_2\ ROA + \beta_3\ ROE + \beta_4\ CAR + \beta_5\ Credit\ Growth$$
$$+\ \beta_6\ Operating\ Efficiency + \beta_7\ COVID - 19\ Crisis + \epsilon_t$$

The results of the regression are tabulated below:

Table 5: Regression Analysis

Variables	*Coefficient*	*Std. error*	*Z-stat*	*P > | Z |*
Credit Risk (Dependent)				
Bank Size	0.081***	0.025	3.20	0.010
ROA	11.703**	4.602	2.54	0.029
ROE	-0.791**	0.320	-2.47	0.033
CAR	-1.241**	0.431	-2.88	0.016
Credit Growth	-0.006	0.028	-0.20	0.847
Operating Efficiency	5.874***	1.299	4.52	0.001
COVID-19 Crisis	0.000	0.005	-0.10	0.923
Constant	-1.729**	0.561	-3.08	0.012

Notes: *** Statistically significant at 1 percent, ** Statistically significant at 5%

R-squared = 0.7714, *F* stat = 4.82

The regression results show that 77% of the variation in credit risk can be explained very highly with the explanatory variables as R^2 is 0.7714. Among the explanatory variables, it is seen that the Bank Size and Operating Efficiency of HSBC have a positive and statistically significant impact at a 1% significance level. Bank size as a positive explanatory variable is consistent with previous studies by Louzis, Vouldis and Metaxas (2012) and Haq and Heaney (2012), who suggested that larger banks are more likely to take on excessive risks than their smaller counterparts. This result indicates that when the bank's total assets base grows, there is an increase in overall credit risk as most of the assets are loans. While COVID-19 impacted revenue, maintaining operating efficiency was critical to the survival and credit-servicing capacity of the bank. The relationship with operating efficiency indicates that when the bank can reduce its operating expenses in proportion to assets, it will also reduce its credit risk, consistent with the studies of Louzis, Vouldis and Metaxas (2012) and Dimitrios, Helen and Mike (2016) who argued that inefficient management led to cumulation of NPLs.

Similarly, profitability and capital adequacy ratios (CAR) were found to have a negative and statistically significant relationship with credit risk at a 5% significance level, consistent with previous studies Radivojevic and Jovovic (2017) and Lafuente, Vaillant and Vendrell-Herrero (2019). The negative relationship between CAR and credit risk is further substantiated by the Basel-III and the bank's resilience to improve the quality of the credit aftermath of GFC 2008 (Rime, 2001; Leung, Taylor and Evans, 2015), also leading to higher quality profits and therefore being a critical aspect of maintaining bank stability and credibility during the COVID-19 crisis (HSBC Liquidity Solutions, 2023). This evidence, along with a decrease in bank size and an increase in operating efficiency during the pandemic, suggests why the health crisis and credit growth rate had a positive but insignificant impact on credit risk during the crisis period.

To conclude, there are many macroeconomic and bank-specific determinants of credit risk, and the list is not limited to the ones discussed above. The select few determinants mostly show a significant relationship with credit risk and more variables that can explain the credit risk can be included for a more robust analysis. Correctly identifying each component that makes up these ratios and risk determinants should be able to estimate the credit risk for a bank and help the stakeholders come to a reasonably confident assessment.

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APPENDIX 1

Summary of numbers for HSBC Banking Group

HSBC Banking Group (figures in millions USD)

Year	Operating expenses	Total Assets	Gross Loans and Advances	Equity	Impaired/ NPLs	EBT
2023	32,070	3,038,677	955,475	192,610	19,354	30,348
2022	32,701	2,949,286	938,463	185,197	19,633	17,058
2021	34,033	2,957,939	1,061,538	206,777	19,071	18,906
2020	34,391	2,984,164	1,055,465	204,995	19,372	8,777
2019	35,000	2,715,152	1,050,031	192,668	13,710	13,347
2018	34,734	2,558,124	998,038	194,249	13,347	19,890
2017	35,050	2,521,771	970,456	197,871	15,470	17,167
2016	38,637	2,374,986	869,433	182,578	18,228	7,112
2015	40,012	2,409,656	934,129	197,518	23,758	18,867
2014	41,249	2,634,139	987,081	199,978	29,283	18,680
2013	39,285	2,671,318	1,007,312	190,459	36,428	22,565
2012	42,927	2,692,538	979,138	183,129	38,671	20,649
2011	41,545	2,555,579	917,371	166,093	41,584	21,872
2010	37,707	2,454,689	979,320	154,915	28,091	19,037
2009	34,467	2,364,452	922,676	135,661	30,606	7,079
2008	38,604	2,527,465	957,503	100,229	25,352	9,307
2007	39,107	2,354,266	1,000,761	135,416	18,304	24,212
2006	33,579	1,860,758	863,109	114,928	13,785	22,086

(contd.)

Measures and formula of credit risk and its determinants

Measure	Formula
Credit Risk	$\frac{NPLs}{Gross\ Loans\ and\ advances}$
Bank Size	Natural logarithm of Total Assets
ROA	$\frac{Earnings\ before\ tax}{Total\ Assets}$
ROE	$\frac{Earnings\ before\ tax}{Equity}$
Capital Adequacy Ratio	$\frac{Equity}{Total\ Assets}$
Credit Growth Ratio	$\frac{Gross\ Lending_T - Gross\ Lending_{T-1}}{Gross\ Lending_{T-1}}$
Operating Efficiency Ratio	$\frac{Operating\ expenses}{Total\ Assets}$