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Bachelor's Thesis Economics and Business Economics

Predicting the Collapse of Credit Suisse

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Abstract

This paper assesses the predictive ability of the CAMELS model with regard to bank failure as well as the significance of its factors concerning the performance of a bank. The failure of Credit Suisse in 2023 was studied, specifically their financial data between 2018 and 2022, and then passed through the CAMELS framework to form ratings that indicated the poor performance of banks. Furthermore, these ratings were plotted against Tobin's Q-ratio, concluding that these ratings were correlated to bank performance. It can be concluded that the hypothesis of the CAMELS rating's ability to predict the failure of Credit Suisse cannot be rejected.

Keywords: CAMELS Model, Bank Failure, Capital Adequacy, Credit Suisse

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1. Introduction

In the month of March 2023, Credit Suisse, one of the largest banks in Switzerland, collapsed. This led to long-term consequences for Swiss financial debt and significant concerns about the reliability of Swiss corporate bonds. It stirred mass panic among bondholders as well as investors and led to significant (16 billion CHF) losses. There are now lawsuits surrounding the bypass of financial laws and an overall questioning of the regulatory procedures. However, these losses could have been predicted, and the affected shareholders could have been warned and informed. There are several models to predict a bank's collapse. In 2008, when Lehman Brothers collapsed, the US Federal Reserve could have foreseen the upcoming collapse and imposed strict measures, accompanied by strict monitoring, by using the CAMELS model (Greenspan, 2008). The CAMELS model is a framework that analyses quantitative and qualitative aspects of a bank's performance to assess its overall condition. The relevance of this study revolves around the consequences of a bank collapse. The collapse in 2008 led to an economic recession, significant turmoil in financial markets, and a freeze in credit markets. Thus, it is of significance whether the risk of the potential consequences of the collapse of one of the world's most systemically important banks could have been foretold by a model that is being used by regulators globally.

Previous papers examining the prediction of bank failure using the CAMELS model investigated whether the collapse of Lehman Brothers was caused by the economic crisis of that time or whether it was a result of its malfunctioning (Christopoulos et al., 2011). The same can be attributed to the failure of Credit Suisse, and whether its collapse can either be attributed to the string of scandals, high-order organisational changes, the pandemic, or inadequacy in its functionality. The CAMELS model includes six factors: Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to market risk (Stackhouse, 2021). Together, these factors evaluate banks' ability to raise capital, provide loans, and the overall soundness of the financial institution. Using the CAMELS model, they concluded that the Lehman Brothers collapse was not only due to the financial environment but also a failure in the organisation's strategy. Thus, using the same model and financial data gathered from their reports, a conclusion can be drawn on whether the Credit Suisse collapse could have been predicted. The CAMELS model is most commonly used by the US Federal Reserve, and this paper can be an extension towards observing the model's reliability in European Markets.

In this paper, the evaluation by Christopoulos et al. in the United States is replicated. However, the CAMELS model is an expansion of the CAMEL model developed by the Uniform Financial Institutions Rating System (UFIRS) and consequently implemented by U.S. banking institutions in the 1980s. Soon, it was adopted by the US Federal Reserve as part of their analysis of financial institutions. Therefore, adapting the model to European institutions scrutinises the reliability of the model in other financial markets. Additionally, the markets before Lehman Brothers' (LB) collapse and before that of Credit Suisse, vary. The size of the institutions varied since Lehman Brothers had over 600 billion dollars in assets and Credit Suisse had a smaller balance sheet. Additionally, their businesses varied in type and size since the first focused on investment banking and trading while the latter focused on wealth management. Finally, the causes of the collapse were different. While LB was heavily exposed to risky assets and mortgages, Credit Suisse had issues with risk management and financial losses. Thus, this paper will investigate whether this model just accounted for the factors that were specific to the LB collapse, or whether the model does indeed account for size, complexity, and the financial environment and eventually predict bank failure. In this paper, the research question *"Does the CAMELS Model Predict Bank Collapse?"* will be answered.

The CAMELS model includes six scores based on the six aforementioned factors, each given a score between 1 and 5. Then each score is weighted and then combined to give an overall CAMELS score, in which the higher the CAMELS score, the healthier the bank. Initially, individual scores are determined for each aspect of the CAMELS score. The capital adequacy score refers to a bank's ability to absorb losses while still having sufficient funds to operate. The capital adequacy ratio is calculated by dividing the bank's Tier 1 Assets (common equity and retained earnings) by its risk-weighted assets (Al-Nahiyan, 2017). Non-Performing Loans are divided by the Total Loans to produce the Asset Quality Score (loans and investments). It provides an assessment of the loans that are more than 90 days due, and hence, banks with a higher ratio indicate poor asset quality since they are at a greater risk of experiencing losses. The Management (risk management and decision-making processes) is represented by the ratio Management Expenses over Sales. The lower the ratio, the better the indication that reliable management is overseeing the bank. The Earning's Score (profitability) is calculated by an equally weighted sum of the ROA (Net Profits / Total Assets) and the ROE (Net Profits / Own Capital). The Liquidity Score, or its ability to meet financial obligations, is calculated by equally weighing. Finally, the Sensitivity to Market Risk, meaning banks' exposure to market risk, is represented by Total Securities divided by Total Assets (Australian Government Department of Finance, 2016). The smaller the ratio, the better the bank's ability to deal with market risk changes. Finally, after each score is calculated, the scores are weighted based on importance and then added to calculate an overall CAMELS score. The above data required for the scores over the past twenty years can be found on the Credit Suisse Annual reports, which are on their official website or are summarised on the ORBIS Bank Focus databases.

The initial hypothesis is that the CAMELS model does predict the Credit Suisse collapse. Furthermore, we predict that the model will reliably account for the changes in factors between the different geographical markets and timing differences. This assumption is based on the different weights given to each factor, i.e., more weight given to sensitivity if the country is liable to natural disasters. This paper will show that the aftershocks could have been minimised, which initiates calls for changes in regulation, laws concerning financial securities, and more communication between global regulators to protect international shareholders. Furthermore, it will also provide a basis for investors on how to efficiently evaluate banks before investing large amounts of money into bonds and other financial instruments. Overall, the prediction of the collapse by the model does enunciate the need for better regulations and confirms that this crisis could have been predicted. There are other factors that lead to bank failure, such as credit risks, foreign regulations, market collapses, and global catastrophes. Furthermore, other models, such as Merton's structural models and logit models, can be used to predict bank failures.

2. Theoretical Framework

2.1 Banks and Bank Failure: Background

A bank is defined as a financial institution that deals with debits and credits. It lends, accepts, and deposits money (Prabhavathi and Dinesh, 2018). Professor Kirby, as cited in Vetrova (2017), describes banks as institutions where advances of money can be made safely and where individuals entrust money when it is not required by them for use. Banks have evolved through numerous stages, from prehistoric times to the present. The first legitimate financial organisation, a bank, was included in the second stage when individuals were anxious to profit and the number of borrowers expanded (Goldthwaite, 1995). The trade growth has increased the number of banks, and consequently, their range of activities has increased. Central banks are now the monetary authorities in charge of managing currency, the money supply, and interest rates (Giuliodori et al., 2020). Banks have a major role in running our financial system. A better-performing bank would lower the cost of capital and accelerate economic growth (Cocris and Ungureanu, 2007). However, when a bank collapses, it can have severe consequences for the financial markets, such as corruption, a lack of economic freedom, increased regulation, and so forth (Federal Reserve Bank of St. Louis, 2021).

Bank failure is the state in which outputs are low, demand for liquidity is high, and agents are worse off in relation to average experience (Williamson, 1988). Illiquid asset holdings, organisational complexity structures, and the liabilities of financial firms are the main factors that cause bank failure (McAndrews et al., 2014). They continue, and say that since banks issue money as liabilities and demandable deposits increase risk, bank failures are frequently worse than non-financial institution failures and result in greater devastation. Wheelock and Wilson (2000) conclude that poorly capitalised banks are at higher risk of failing. Furthermore, banks with higher ratios of loans to assets are also at higher risk of failing. Finally, they conclude that managerially inefficient banks also have a higher probability of failing in terms of cost and technical inefficiency. Various methods of predicting bank failure exist, including logit and probit models, AI models, and machine learning methods (Manthoulis et al., 2021). Martin (1977), as cited in Liu et al. (2021) used a univariate logit model to predict bank failure in the US. Tam (1991) used A.I. neural networks from failed and "non-failed banks" to predict a model that would identify struggling banks that could potentially fail.

2.2 The Development of the CAMELS Model

2.2.1 The CAMEL Model

The CAMELS model was initially developed by the Federal Financial Institutions Examination Council (FFIEC) in the United States as the CAMEL model without the inclusion of sensitivity to market risk. It was first put into effect in 1979, as a measure of supervisory information and went on to be used by the Federal Reserve System, the Office of the Comptroller of the Currency (OCC), and the Federal Deposit Insurance Corporation (FDIC). It was then accepted by the National Union Credit Administration in October 1987 (UFIRS, 1977). Barr et al. (2002) describe the CAMEL model as an effective internal supervisory tool for evaluating the soundness of a financial firm, based on identifying those institutions requiring special attention or concern. Kabir and Dey (2012) highlight the increasing use of the CAMEL rating internationally to evaluate the strength of commercial banks. Majumder and Rahman (2017) emphasise that the strength of the CAMEL factors reveals the overall strength of the bank. The CAMEL model has been used to evaluate the soundness of many banks internationally. Mishra et al. (2013), as cited in Majumder and Rahman (2017), used it to rate the bonds and fixed deposits of the State Bank of India. Tripathi et al. (2014) analyzed the Axis and Kotak Mahindra Bank using the CAMEL rating and the t-test to compare financial performances. Dzeawuni and Tanko (2008) analysed the financial performance of Nigerian Banks over the prior two years. Several other studies used the CAMEL rating system and led to the conclusion that the CAMEL rating system is a standardised test for bank performance (Jaffar and Manarvi, 2011). However, in the early stages of the model's development, it served purposes beyond determining if a financial organisation was sound.

Swindle (1995) used the CAMEL model to evaluate the effectiveness of the regulators in commercial banks by exploring whether regulators influenced the changes in the capital of a bank once the weak capital position of a bank had been realised. Previous studies of regulatory pressure included using regulatory opinions as a measure of regulatory pressure, which led to the misclassification of capital adequacy and thus a biased result. Thus, the CAMEL capital adequacy rating would provide a better proxy for the capital rating as it is confidential. Johnson and Weber (1977) studied whether the CAMEL rating reflected superior information. They predicted a model to determine the difference in stock returns, before and after the disclosure of the returns. The forecasted error patterns from these models reflected that the lack of inclusion of sensitivity to the market allowed for consistent stock returns, despite the publication of the CAMEL ratings. Hirschhorn (1987), Berger and Davies (1998), and Flannery and Houston (1994) further argued that the CAMEL rating did not reflect the stock return but was significantly related to the overall rate of return. This suggests that both regulators and the public used the same set of information or that there was a leak of data during that period. Cargill (1989) determines that the CAMEL ratings developed by regulators using proprietary and confidential information are often comparable to the ratings available to the market. He further concludes that the rating would be just as reliable if developed by individuals using publicly available information and would thus provide valuable insight into the financial soundness of the institution regardless. He concludes that the ratings act instead as a proxy for market information, banks' interest rates, and their credit risks.

More studies have been conducted on the constraints of the CAMEL model outside of the foundation articles from the 20th century. Cole and Gunther (1998) further reflect on the lack of influence of proprietary information on the determined rating. They conclude that this leads to a lack of accuracy in the prediction of bank failure, particularly, the accuracy of a CAMEL rating to predict failure is a decreasing function of the length of time since the rating was assigned (Cole and Gunther (1998). Furthermore, Jones and King (1995) find that financial reports that use book values often overstate a bank's true market value, and thus frequent valuation would be necessary. However, the Federal Deposit Insurance Corporation argues that the reduction of regulators' resources leads to an increase in the time between valuations as well as the cost of an individual valuation. Thus, considering the lack of influence of proprietary information, the frequent high-cost revaluation, and the deterioration of the validity of the rating itself over time, the CAMEL model was revised on January 1st, 1997, to the CAMELS model, including the sensitivity of an individual bank to market risk (*S*) (Rose and Hudgins, 2010).

2.2.2 The CAMELS Model

The *S* factor accounts for how a bank responds to changes in interest rates, equity prices, and foreign rates (Boateng, 2019). The six categories of ratios calculated in the CAMELS model are as follows: Capital (C), Asset Quality (A), Management Quality (M), Earning Ability (E), Liquidity (L), and Sensitivity (S). There has been extensive research on the significance of the

CAMELS criteria in determining the soundness of a financial institution. Capital Adequacy reflects the banks' ability to bear unexpected losses and meet their financial obligations (Abbas et al., 2019). There is also a minimum amount of capital that is required to address the resulting risks (*Global Banking Regulations and Basel Accords,* as cited in Al-Amin, 2010). Assessment of Asset Quality will result in a better valuation of the liquidity and capital of the bank (Shaddady and Moore, 2019). Furthermore, it reflects the ability to generate returns as well as the level of risk associated with borrowing and Investments (Handorf, 2016). Management Quality is regarded as the key factor in evaluating a firm's stability (Cargill, 1989). It further reflects the ability of the Board of Directors to manage risk. Earnings are the realised profit and their contribution to the capital increase (Gilbert et al., 2002). Earnings ability is the most important factor in evaluating a firm's performance (Rostami, 2015). Earnings ability reflects the ability of the bank to make profits and, thus, its ability to provide returns to the bank's shareholders. Liquidity is the ability of firms to meet funds claimed by depositors (Rostami, 2015). It is preferable for shareholders if banks can provide the funds without having to sell securities at low prices or borrow at high interest rates, highlighting the importance of the bank being reasonably liquid.

There are several advantages and disadvantages to using the CAMELS model to predict bank failure. The CAMELS model leads to reduced evaluation time since it only focuses on six factors and thus omits the inclusion of unwanted variables (Al-Amin 2010). Furthermore, Dhehrb (2010) highlights that the model relies on digital assessment rather than reporting style, which increases their credibility due to the overvaluation of firms in the books mentioned before. Derviz and Podpiera (2008) highlight that the ratios used to evaluate each factor are based on personal judgment. Despite the experience of a regulator, human judgement does raise the probability of inaccuracy in the results, since there could be better ratios that would analyse a specific firm's factor better. They also emphasise the dependence of the rating on a firm's asset size. In theory, if a firm's asset size changed dramatically, the weight and relative group they would be assigned would change, thus causing a change in their classification. However, their financial position could remain the same, causing an inaccuracy.

The inclusion of sensitivity into the model has increased the relevance of the model itself. During the financial crisis of 2007, the assessment of market risk associated with changing interest rates concerning banks was key to assessing stability (Kandrac, 2014). The CAMELS model is now being used for both onsite and offsite monitoring. Doumpos and Zopounidis (2010) state that the central banks of countries use the model while assessing their local banks. Pasiouras et al. (2006) also highlight that the model is traditionally used by auditors and bank regulators. Overall, it has been judged as an efficient tool for analysing both bank performance and failure rates (Salhuteru and Wattimena, 2015). Regarding bank performance, Venkatesh and Suresh (2014) evaluate the performance of commercial banks in Bahrain. Rozzani and Rahman (2016) use the model to evaluate the earnings on assets for a set of commercial banks in Malaysia. Boateng (2019) assesses the performance of ten Ghanaian banks over seven years, to highlight the various effects each factor of the CAMELS model has on the performance of the bank. An important note is the difference in ratios used by authors to assess the various ratings, despite studying overlapping banks in the same geographical locale. Roman and Sargu (2013) performed an analysis of the financial soundness of the Commercial Banks in Romania. A year later, Rodica-Oana (2014) performed a similar analysis on Romanian banks with some overlapping institutions. While the initial paper assessed capital based on the equity-to-total asset ratio, the latter considered a solvability ratio to be more appropriate. Another case would be when they assessed the management rating. The prior paper considered operating expenses to asset ratios and interest expenses to deposits, highlighting that they considered the expenses on managerial decisions to be what indicated management quality. However, the latter is considered a debt to deposits as well as a return per employee. This stark difference in the foundation ratios used to calculate the ratings, despite the same institutions, highlights the importance of personal judgement and, furthermore, the need to assess a bank carefully before selecting the ratios used.

Overall, the observed main reasons for bank failure and consequently the important factors to evaluate in failure prediction are Capital Adequacy (C), Asset Quality (A), and Management (M), all of which are important factors in the CAMELS model. The CAMELS model has been used on several occasions to predict bank failure (Stackhouse, 2021). Lane et al. (1986) used the model along with a hazard model, attempting to predict the failure of 130 banks in the United States. Kunt and Detragiache (1998) identified the main reasons for bank failure in developed and developing countries to high inflation and low inflation rates using the CAMELS model in par with a logit model. Molina (2002) also used the model, along with the hazard model, to predict the failure and state of commercial banks in Venezuela. She concluded that banks with a higher ROA and more investments are less likely to fail. Overall, the CAMELS model has been used to successfully predict or observe struggling banks and, thus, bank failure. However, it is important to note that it is a precautionary model, and therefore bad ratings do not guarantee failure and good ratings do not guarantee stability. This leads to testing the following hypothesis:

H_1: The CAMELS model will provide ratings that indicate the poor performance of Credit Suisse and consequently predict its failure.

3. Data and Methodology

3.1 Data

3.1.1 Data Collection

The data sample is gathered from the consolidated financial statements, annual reports, quarterly reports, and interim reports that are published by the Credit Suisse AG group. The data from their consolidated companies is omitted, and only the bank data is used to remove any bias in the results (i.e., additional capital brought into the group from companies that are not on par with the bank). The reports gathered are between the years 2018 and 2022. The reason the data from 2023 is being omitted despite being published is that since the collapse occurred in March 2023, the data collected post-bank failure would be immaterial in predicting it. Furthermore, the bank collapse would be highly influential in reducing the money circulating in the bank thereafter, and thus a large part of the data from 2023 would act as outliers and bias the results. There would be five observations, one each year, and thus five yearly ratios calculated and consequently five ratings. The data required for the capital adequacy ratios was sourced from the consolidated balance sheets, the capital adequacy report, and the Bank for International Settlements (BIS) sections. The BIS statistics are issued by the Basel (*Global Banking Regulations and Basel Accords*). Committee on Banking Supervision, which is the standard setting institution for banks in Switzerland. The data required for the asset quality ratios was gathered from Section 18 of the Consolidated Financial Reports, which includes information on loans, allowance for loan losses, and credit quality. The Management ratio is calculated from data under Section 11 of the Consolidated Financial Reports titled “Compensation and Benefits” which provides information on salaries, pensions, and post-retirement. The data required for the

Earnings ratio is calculated from Sections 8 and 9 of the Annual Reports and includes information on trading revenues, investments, loan revenues, and interest revenues. The information for the liquidity ratios is sourced from the balance sheet posted in the annual report, along with information consolidated from the quarterly reports regarding deposits. Finally, the Sensitivity ratios are sourced from Section 14 and Section 16 of the Consolidated Financial Reports, which include information on securities lent or borrowed, subject to repurchase, and investment securities.

3.1.2. Ratio Calculations

The Capital Adequacy Ratio (CAR) in Switzerland, according to Basel III regulation, is meant to be no less than 8 percent. The ratio will be calculated using the following equation:

$$CAR = \frac{Tier\ 1 + Tier\ 2}{Risk{-}Weighted\ Assets}$$

In the equation above, Tier 1 (capital), as defined in Basel III, is the sum of common shares, comprehensive income, stock surplus, regulatory adjustments, and retained earnings (*Financial Stability Institute*). Additionally, it includes the sum of capital instruments and their related surplus. Tier 2 (capital) forms the bank's supplementary capital (Christopoulos et al., 2011). It includes capital derived from bonds issued by the bank as well as any loan loss provisions that qualify. The Risk-Weighted Assets, along with the Tier 1 and Tier 2 capital, are expressed in millions of CHF throughout. The higher the ratio, the stronger the bank's capital base in comparison to its risk.

The Asset Quality Ratio (AQR) refers to evaluating risk concerning the bank's portfolio. It also takes into account any doubtful claims associated with the bank's ability to detect and regulate credit risk (Christopoulos et al., 2011). The ratio will be calculated using the following equation:

$$Asset\ Quality\ Ratio\ = \frac{Total\ Non{-}Performing\ Loans - Provisions}{Total\ Loans}$$

Basel III considers 90 days to be a critical point in loan repayment (*Global Banking Regulations and Basel Accords*). Therefore, non-performing loans are considered to be those that have fallen over the 90-day benchmark. Provisions are funds that are set aside by the fund to cover any unexpected losses and could include bad debt provisions, income tax provisions, and so forth. Therefore, the lower the ratio, the better the bank's ability to repay loans, implying a good-quality portfolio. The net non-performing loans as well as total loans are expressed in CHF millions.

Management quality (MQR), as previously stated, is critical to bank performance. It displays the ability of the bank to deal with risk, make judgments on investments and securities, and the overall smoothness of the operation. The ratio will be calculated using the following equation:

$$Management\ Quality\ Ratio\ = \frac{Management\ expenses}{Sales}$$

Management expenses include salaries, pension expenses, compensation, and bonuses given to managerial staff. It also includes all operating expenses borne by the bank. The Sales account is for all interest expenses borne by the bank and is sourced from the Profit and Loss Statement. The ratio gives the percentage of Sales Revenue that is spent on operational expenses and provides an insight into how much is being spent to ensure smooth operation. A high rating implies smoother operation and better bank perforation. Management Expenses and Sales are expressed in CHF millions.

The Earnings Ratio implies the profitability of the bank and the ability of the bank to generate earnings for its shareholders as well as an entity. They also infer if a bank can support any future expenses and whether it will expand into other financial activities. It further assesses the bank's ability to absorb losses if and when they occur. The ratio will be calculated using the following equation:

$$Return\ on\ Assets = \frac{Net\ Profits}{Total\ Assets}$$

$$Return\ on\ Equity = \frac{Net\ Profits}{Own\ Capital}$$

The ROA ratio implies whether the bank's asset management is sufficient to generate profits. A range of 1.5% to 2.5% is deemed to be a sufficient level of asset management. The ROE ratio implies the bank's ability to generate profits from its own capital. The higher the ratios, the better the banks' ability to generate profit, which implies better performance and a base for stability. Net Profits, Total Assets, and Own Capital are expressed in CHF millions.

The Liability Ratio implies the ability of the bank to liquidate its resources in the event of a loss and minimise its losses in that process. The ratio takes into account the bank's liabilities. The ratio is given as follows:

$$Loans\ to\ Total\ Deposits = \frac{Total\ Loans}{Total\ Deposits}$$

$$Circulating\ Assets\ to\ Total\ Assets = \frac{Circulating\ Assets}{Total\ Assets}$$

The Loan to Total Deposits (LTD) ratio demonstrates the banks' ability to manage their deposits and provide loans, as well as their reliance on interbank markets. The lower this ratio, the better the liquidity of the bank. However, a score less than one implies loan security since deposits themselves cover loans (Christopoulos et al., 2011). The Circulating Assets to Total Assets (CTA) ratio shows the ability of the bank to cover losses that cannot be compensated by directly available assets. The higher this ratio, the better the bank's liquidity. Total Loans, Total Deposits, and Circulating Assets are expressed in CHF millions.

The Sensitivity Ratio (STM) displays how sensitive the bank is to interest rates and foreign currency exchange rates, as well as how they affect a bank's profit margins. The following equation is used to calculate the ratio:

$$Sensitivity\ to\ Market\ = \frac{Total\ Securities}{Total\ Assets}$$

Due to increasing international relations between banks, their dependency on foreign markets has a huge influence on their performance and viability. The ratio implies the change in the bank's portfolio concerning interest rates and other market movements. A lower ratio implies that the bank deals with market fluctuations and risks appropriately, thus implying stability. A higher ratio implies that the bank is susceptible to market risks.

Tobin's Q-ratio is going to be used as an indicator for bank performance and is given by the following formula:

$$Tobin's\ Q\ = \frac{Market\ Value\ of\ Equity}{Book\ Value\ of\ Assets}$$

It is useful for measuring bank performance for those banks with significant asset components, like Credit Suisse, since it accounts for how the bank's assets are being used to generate market value. The Q-ratio also affects market performance since it signals investors that they can generate profits and thus provides a good indicator of how well the bank is performing both in the market and on its books.

Table 1.
Summary Statistics

Variable		Mean	SD	Min.	Max.
C	CAR	0.3451731	0.0289197	0.3045779	0.3753429
A	AQR	0.0002376	0.0013444	-.0013351	0.0019496
M	MQR	6.4395570	3.1488580	3.066700	11.0705600
E	ROA	0.0285021	0.0012604	0.0269665	0.0303498
	ROE	0.4789354	0.1246952	0.3138254	0.6638836
L	LTD	0.8155526	0.1531336	0.7276097	1.0878240
	CTA	0.1543029	0.0393825	0.1278132	0.2165424
S	STM	0.1668217	0.0332075	0.1197893	0.2075825
Q		0.5952081	0.2543154	0.2483703	0.9322634

Note. The summary statistics are included for each ratio of the CAMELS model along with those for Tobin's Q-ratio. They include information that reflects the central tendencies, variability and ranges for each of the variables. The quartile values and such have been omitted due to lack of significance with regards to the outcome of this paper. The values have been sourced from STATA, while the data required for the calculation of the ratios themselves has been sourced from the financial reports of the Credit Suisse group. All values in the above table are up to seven decimal places to account for the differences between each statistic.

3.2 Methodology

3.2.1 CAMELS Model

Initially, using the data and formulas calculated above, an individual ratio for each of the CAMELS factors is calculated for every year. Furthermore, a yearly CAMELS score is also calculated to highlight the progression and performance of the bank between the years 2018 and 2022. The bank is then judged based on the following CAMELS ratings table and then assessed by the following weights:

Table 2.
CAMELS elements weight factors

Item	C	*A*	*M*	*E*	*L*	*S*
Weight	*0.20*	*0.20*	*0.25*	*0.15*	*0.10*	*0.10*

Note. The weights of each category have been sourced from Rostami (2015). The weights do change based on regulatory opinion, stress testing and so forth. Based on the size and location of the banks, the weightage used for each bank does indeed change. These ratings have been used to assess a similarly sized European bank and thus would be appropriate in assessing Credit Suisse in terms of all the factors.

The weights have been determined from previous literature and are based on the deemed importance of each of the factors on bank performance. Sensitivity has historically been assigned the lowest weight, and Capital and Assets have often been assigned the highest weights, due to the importance of holding capital and asset management in the bank's performance. An initial regression is performed between Tobin's Q-ratio and the overall CAMELS score to determine the trend of bank performance relative to the overall score. The reason for two separate regressions on the same calculation is to account for possible collinearity among the independent variables if regressed separately. The overall CAMELS score has been calculated per year using the following formula:

$$CAMELS = 0.2C + 0.2A + 0.25M + 0.15E + 0.10L + 0.10S$$

The trend of the individual ratings per individual year will be mapped over the five years through a linear regression against Tobin's Q-ratio, the dependent variable. The equation for the regression based on these weights is as follows:

$$Tobin's\,Q = 0.2C + 0.2A + 0.25M + 0.15E + 0.10L + 0.10S$$

Before the regressions, both the Tobin's Q-ratio and the CAMEL ratios will be tested for normal distribution using the Shapiro-Wilk test under the null hypothesis that the data follows a normal distribution. The Shapiro-Wilk test is very sensitive to large sample sizes, and thus even a slight deviation from normality will result in the rejection of the null hypotheses. However, due to the small sample size being considered, this test will provide the most accurate conclusion on whether there is evidence that the null hypothesis can be rejected. Furthermore, to test for autocorrelation, the model will be tested by the LM Lagrange test of validity, under the null hypothesis that the restrictions of the model are valid. The test follows a chi-squared distribution and often assumes that the data is normally distributed. Finally, to test for heteroskedasticity, the White test is used, under the null hypothesis that the residuals exhibit constant variance across all the independent variables. It allows for checking the accuracy of parameter estimates, standard errors, and hypothesis tests.

4. Results

4.1 CAMELS Ratios

The ratios, including Tobin's Q-ratio, were calculated using observed financial data from the Credit Suisse Reports. The manner in which to interpret them can be found in Table 3. The results of the CAMELS Scores for each year are also presented in Table 3 and were calculated using the aforementioned equation. The results presented in Table 4 are those of an OLS regression model and thus can be interpreted through its coefficients.

Table 3.
The CAMELS Ratios for Credit Suisse (2018-2022)

Variable		Year				
		2018	2019	2020	2021	2022
C	CAR	0.305	0.327	0.353	0.375	0.391
A	AQR	0.195	0.108	-0.134	-0.082	0.032
M	MQR	7.813	5.988	11.071	4.260	3.067
E	ROA	0.270	0.287	0.278	0.303	0.287
	ROE	0.453	0.485	0.663	0.479	0.314
L	LTD	0.770	0.757	0.735	0.728	1.088
	CTA	0.129	0.128	0.171	0.217	0.128
S	STM	0.208	0.188	0.161	0.158	0.120
Q		0.608	0.705	0.932	0.483	0.249
CAMELS		2.116	1.664	2.951	1.241	0.938

Note. The above table displays the values of each of the CAMELS factors between the years 2018 to 2022. All the information has been sourced from the financial statements of Credit Suisse. All values have been rounded to three decimal places, except those that are in scientific notation. All values are considered statistically significant since they have not been predicted but calculated. Furthermore, Tobin's Q-ratio and the accompanying overall CAMELS value for all five years are also included and considered to be statistically significant. The values of the CAMELS have been calculated using the equation presented in the Methodology. The values of the AQR have been multiplied by 100 for better notation. The values of the ROA have been multiplied by 10 for better notation.

4.2 Regression of Bank Performance on the CAMELS scores

Table 4.

OLS Regression Results

Tobin's Q	Coefficient	t	P > | t |	95% conf. interval	
CAMELS	0.296** (0.073)	6.170	0.009	0.143	0.449
Constant	0.068 (0.140)	0.570	0.610	-0.313	0.448
F-statistic	38.120				
Prob > F	0.009				
R-squared	0.846				
Root MSE	0.115				

Note. The above table displays the regression results for the CAMELS overall scores for the years (2018-2022). The results have been sourced from STATA and the data used is sourced from the financial statements of the Credit Suisse group. All values have been denoted up to three decimal places.

The model provides an R-squared value of 0.846, which means 84.6% of the variability in bank performance is indicated by the CAMELS scores. However, this high of an R-squared value indicates overfitting, thus meaning that the model accounts for additional noise beyond the true relationship between the two variables. An MSE of 0.115 is an indication of a well-fitted model, since it is low, thus highlighting that the data points predicted by the model and the actual data points are not far apart. The high F-statistic of 38.120 with an accompanying p-value of 0.009 (<0.05), connotes that at least one of the factors has a statistically significant effect on the dependent variable and also infers that the overall model is significant.

The positive coefficient indicates a positive relationship between the two variables. To be specific, an increase in CAMELS score by one unit leads to an increase in bank performance by

0.296. Therefore, with respect to Capital, Management, Liquidity, and Sensitivity, the CAMELS score does have a positive impact on bank performance. However, in the case of Asset Management and Earnings, the model deems them to have a negative impact on bank performance since a lower ratio (negative) in these categories would theoretically indicate better bank performance. Finally, since the t-statistic of the coefficient is high and the p-value is less than 0.05, it can be concluded that the CAMELS variable has a significant positive effect on Tobin's Q-ratio and thus bank performance. Furthermore, as can be seen in Figures 1 and 2, both Tobin's Q-ratio and the CAMELS model seem to fall on a negative gradient as the years get closer to 2023. In conclusion, the hypothesis that the CAMELS model predicts poor performance and thus the hypothesis that it successfully predicts the bank failure of Credit Suisse cannot be rejected.

Figure 1.
The movement of the CAMELS score of Credit Suisse (2018-2022)

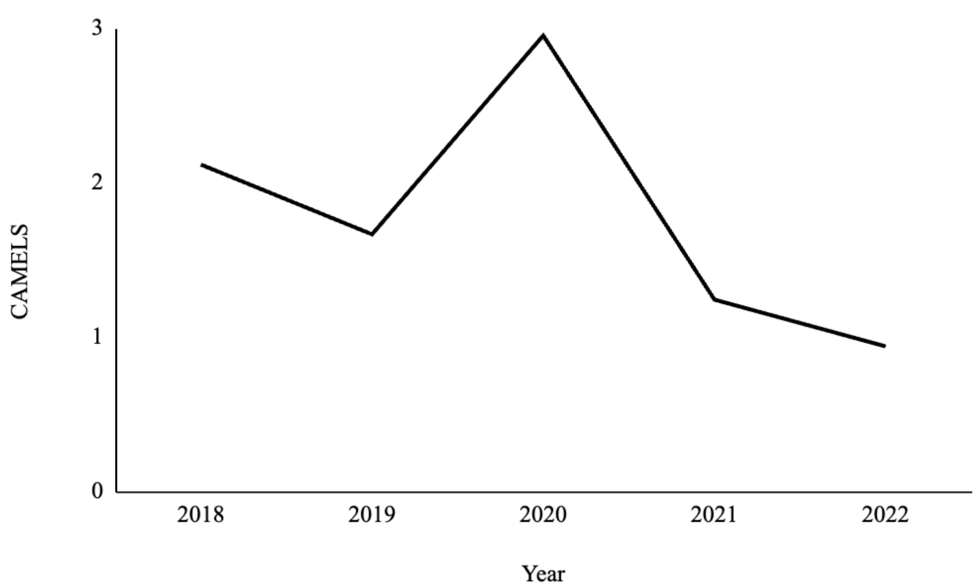
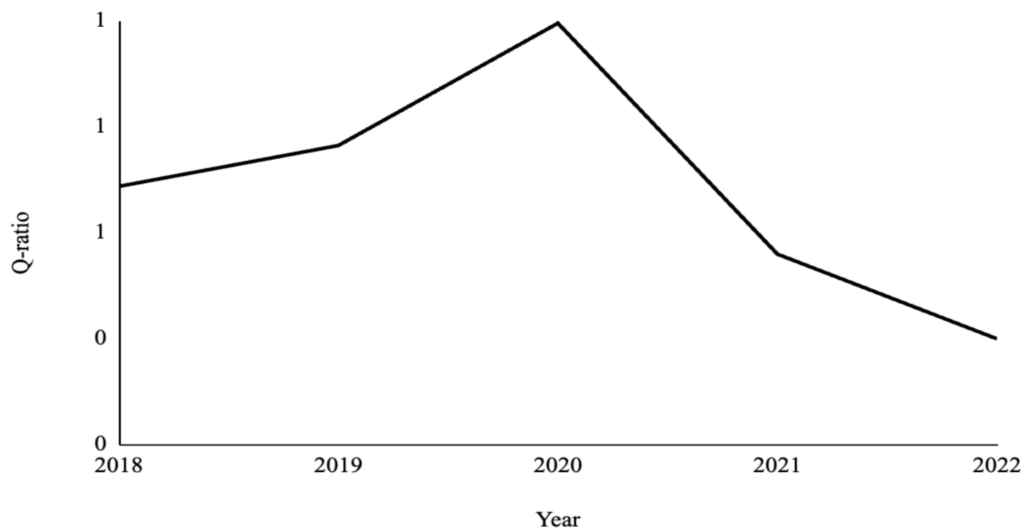


Figure 2.
The movement of the Q-ratios of Credit Suisse (2018-2022)



The results of the regression between Tobin's Q-ratio and the individual CAMELS coefficients are given below:

4.3 Regression of Bank Performance on CAMELS ratios

Table 5.
The OLS Regression Results of the Tobin's Q-ratio on each CAMELS factor

Tobin's Q	Coefficient
Capital Adequacy	-9.018
Asset Quality	-
Management Expenses	-0.085
Earnings	9.701
Liability	2.833
Sensitivity to Market Risk	-
Constant	0.422

Note. The above table displays the regression results between the Tobin's Q-ratio and the individual CAMELS factors. The results are sourced from STATA using the data obtained from Credit Suisse's financial statements. The data represents financial information calculated from the year 2018 to 2022.

They are insignificant at any level of significance. The coefficients for Asset Quality and Sensitivity to Market Risk have been omitted due to collinearity. The index for the significance is as follows *p<0.05 **p<0.01 ***p<0.001.

The above results are insignificant, and it can be observed that there is perfect collinearity due to the omitted coefficients. However, the magnitude and direction of each of the factors still provide important insight into how each of the factors interacts with bank performance. The Earnings coefficient of 9.701 shows that the ability of the bank to generate profit and income for its shareholders has a significant impact on bank performance, which is similar in theory to previous literature. However, the Capital Adequacy coefficient of -9.018 does not agree with previous findings. Anyhow, since the results of this table are insignificant and since the F-statistics could not be calculated, it can be assumed that the results of this regression are not accurate. However, it is important to note that the R2 value of 1 implies that the independent variables together perfectly explain the dependent variable, thus denoting that the CAMELS factors do explain bank performance well.

5. Discussion

The results conclude that the CAMELS score could have successfully predicted bank failure. These results are similar to those of Christopoulos et al. (2017), who concluded that the failure of Lehman Brothers in 2008 could have been predicted. They also follow the same pattern, where the CAMELS score accurately depicts the drop in quality in the bank the year prior to its collapse. They also use a similar rating system where the higher the CAMELS score, the better the performance of the bank. However, there were discrepancies in the models with regard to the ratios chosen due to the nature and size of the financial institutions being analyzed as well as the availability of the information. Despite Lehman Brothers being a different kind of financial institution, the interpretation that the CAMELS model can provide an indication of whether the bank is performing poorly and thus its prediction capabilities still stands. This paper further concludes that the CAMELS score and Tobin's Q-ratio have a significant correlation, which is also concluded by Rostami (2015). Furthermore, their use of the ratio as a performance indicator and its positive relationship with CAMELS are comparable to the results of this paper. However, their methodology of calculating Q involved predicting using various weights for each CAMELS score and then regressing it over five years, while this model instead calculates Tobin's Q-ratio prior to the regression. Despite, the difference in methodology, the conclusion that Tobin's Q-ratio is a reliable indicator of bank performance can be considered reliable. Boateng (2019), while using the CAMELS ratio to analyze the performance of ten Ghanaian banks, indicates that Earnings had the highest effect on performance and sensitivity had the lowest. While this paper does coincide with the conclusion that earnings do have the highest effect on bank performance, the significance of sensitivity has not been defined.

6. Conclusion

The reliability of the CAMELS model in predicting bank failure has been investigated in this paper. Previous research has shown that the CAMELS model does indeed predict bank failure successfully, but since there is a limitation in the amount of financial information that is publicly available as well as privacy laws that limit the publication of such predictive reports post-collapse, especially when considering a large bank such as Credit Suisse, the extent of the accuracy of the CAMELS model has yet to be seen. Therefore, the question that this paper intends to answer is "*Does the CAMELS Model Predict Bank Collapse*?".

To answer the research question, financial data with regard to capital adequacy, asset management, earnings, liquidity, and sensitivity to market risk, has been collected over the five years prior (2018-2022) to the collapse of Credit Suisse. Using the data collected, from the banks of financial statements and reports, ratios were calculated for five years for each individual rating of the CAMELS model. Finally, each of the years' ratios was regressed against Tobin's Q-ratio. Tobin's Q-ratio was used as an indicator for bank performance, and thus the model would demonstrate whether the CAMELS model accurately captured the rise and fall of bank performance over the five years. This study concludes that each of the CAMELS scores have a significant impact on bank performance, and thus an analysis of these indicators would provide an accurate representation of the performance of the bank and thus a reliable predictor of whether a financial institution is stable or liable to collapse. Combined with previous literature, the use of the CAMELS model in predicting bank failure should be cemented. Furthermore, it also concludes that financial regulators could have predicted the failure of Credit Suisse prior to its collapse and thus calls for a change in regulatory procedures.

7. Limitations

A potential limitation of this study is that the information available to the public is constrained. To be specific, Tier 2 assets were a crucial factor in calculating the capital adequacy ratios for each year. However, a large part of Tier 2 assets, in theory, is undisclosed capital reserves and thus unavailable on any financial statements. Thus, the revaluation reserves and hybrid instruments were used as proxies for Tier 2 assets in calculating Capital Adequacy ratios. Another, limitation in data availability can be identified while calculating Tobin's Q-ratio. Tobin's Q-ratio often includes the replacement costs of a firm's assets as its denominator. This can easily be accounted for if the institution being analyzed is a manufacturing company, or per se, a company that has a large amount of physical assets. However, in the case of a bank, where a large proportion of its assets are financial instruments, the replacement costs for said assets are hard to predict. Thus, in this study, the book value of assets is used to substitute for the replacement cost of assets. Using another indicator of bank performance, such as ROA or ROE, might prove to be a better indicator in further studies since it does not include factor substitution. Furthermore, using the book value of assets does not capture the market value of the assets, and since financial instruments are volatile over time, the value gained or lost over the period of time since acquisition is not accounted for. Tobin's Q-ratio is often used to indicate investor intent, and using the book value of assets does not account for market movements, and thus could be an inaccurate measure of bank performance. Finally, the CAMELS score only predicted poor performance in the last year, prior to the collapse. Whether this can be regarded as sufficient time in order to "rescue" the bank cannot be determined. In further studies, using a different indicator for bank performance as well as other ratios for each CAMELS rating within the CAMELS score could provide a better representation of the movements of the banks' performance as well as a better indication of which factors significantly impact bank performance.

8. References

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9. Appendices

The normality, homoscedasticity, and autocorrelation of the data are also tested for and are presented in the below tables. The Shapiro-Wilk test for normality has been performed for both CAMELS and Tobin's Q-ratio. Since the p-values are high (0.815 and 0.999), the data can be assumed to be normally distributed and thus can be assessed and evaluated using tests that assume normality. Furthermore, due to the low p-values assessed in the Lagrange LM test, whose results are presented in Table 6, it can be assumed that there is not enough evidence to suggest autocorrelation among the residuals. Finally, the results of the White test, which are presented in Table 7, due to the high p-value of 0.365 (>0.05), suggest that there is not enough evidence to suggest that there is heteroscedasticity amongst the residuals.

Table 5.
Shapiro-Wilk Test Results (Normality)

Variable	Obs	Q	V	z	Prob > z
CAMELS	5	0.961	0.460	-0.896	0.815
Tobin's Q	5	0.998	0.024	-3.024	0.999

Note. This table includes the test results of the Shapiro-Wilk test for normality. The variables being tested for normality are CAMELS and Tobin's Q. The significance level for the test is set at $\alpha = 0.05$. The analysis was performed in STATA and the data used for this analysis was sourced from the financial statements of the Credit Suisse group from the years 2018 to 2022.

Table 6.
LM Lagrange Test Results (Autocorrelation)

Source	Chi^2	df	p
Heteroskedacity	2.020	2	0.365
Skewness	0.470	1	0.495
Kurtosis	0.630	1	0.426
Total	3.120	4	0.539

Note. This table shows the test results for the LM Lagrange test for Autocorrelation. The regression model being tested is the regression between the Tobins-Q ratio (bank performance) and the CAMELS ratio. The significance level for the test is set at $\alpha = 0.05$. The analysis was performed in STATA, and the data used for this analysis was sourced from the financial statements of the Credit Suisse group from the years 2018 to 2022.

Table 7.

White's Test Test Results (Heteroskedacity)

Chi^2	2.020
Prob > Chi^2	0.365

Note. This table provides the test results for White's Test for heteroscedasticity. The regression model being tested is the regression between Tobin's Q-ratio (bank performance) and the CAMELS ratio. The significance level for the test is set at $\alpha = 0.05$. The analysis was performed in STATA, and the data used for this analysis was sourced from the financial statements of the Credit Suisse group from the years 2018 to 2022. The test follows a Chi^2 distribution.