Impact of Price Indexes on Stock Market Prices of Banks in Financial Crises

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Abstract: - During times of crises, stock markets often experience heightened volatility, and the banking sector is particularly susceptible. This study aims to investigate the impact of index values on the daily closing prices of five banks during five major financial crises in recent decades, using logistic regression analyses. The results show that in five crisis periods, different indexes have a significant impact on the daily stock price of banks. Although there is no pattern found for different crisis periods because each bank has different investment instruments, the index, ind38- CFMRC (VWI) Over $2, seems to have a highly significant impact on the crisis periods I-IV and ind37- CFMRC (DEWI) Over $2 plays a significant role in predicting the outcomes. The findings indicate that banks should give particular focus to their investment instruments, particularly value-weighted indexes (VWI) over $2 and equal-weighted indexes (DEWI) over $2 when any indications of a crisis arise. This is crucial because these index values influence the daily closing prices of banks and could potentially contribute to economic crises. Moreover, larger banks are more sensitive to changes in the index values than smaller banks, attributed to variations in their investment amounts.

Key-Words: - Financial crises, Daily closing prices of banks, Indexes, Logistic regression, Value weighted index over $2, Equal weighted index over $2.

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1 Introduction

Economic crises drastically affect everything in socio-economic life. During crises, the unemployment rate, prices, bankruptcies, and insolvencies increase, whereas GDP, production, and purchasing power decrease. The stock market also experiences significant volatility in crisis periods, [1]. Index values are considered critical indicators of the stock market's performance and can have a significant impact on individual stock prices, including banks, [2], [3]. Banks are integral players in the financial system and their performance is closely tied to the health of the broader economy. During the crisis periods, the stock market indexes fluctuate, going up and down, these lead to significant drops in market capitalization and stock prices and increases in volatility and risk, often resulting in large losses for investors. Since the banks are seen as a fundamental stone of the overall health of the economy, banks can be heavily impacted by the crises. Therefore, it is essential to understand the relationship between the daily closing price of banks and index values and also how the crises have an impact on the closing price of banks. This can help investors and financial institutions make more informed decisions about buying or selling bank stocks during crisis periods.

Stock prices are influenced by many economic factors, such as investors' psychology and expectations, the macroeconomic conditions of a country, the movement of other stock markets, political events, etc., [3]. In the stock market, investment instruments in portfolios, such as stocks, bonds, mutual funds, and other derivative instruments are the main factors that affect the daily closing price of banks, [1]. In the stock market, indexes are the main indicators and they have a fundamental role in the daily stock prices of banks. Stock prices change moment by moment in response to any kind of activity, such as economic factors, industry performance, news, and investor sentiments, [4]. “The price of a stock is largely determined by supply and demand.” With high demand, the stock price tends to up, and with high supply, the price tends to go down, [4], [5].

The impact of index values on the daily stock prices of banks is a fundamental area of investigation for investors and financial institutions. This study aims to provide valuable insights for banks and investors regarding their investment strategies during crisis periods and the impact of various indexes on their investment portfolios. For this purpose, this study examines the effect of index values on the daily closing prices of five major banks in Canada during five different crisis periods, using logistic regression (LR) analysis. By utilizing LR, the study provides valuable information on the fluctuation of stock prices of banks during the crises.

The remainder of this paper is organized as follows: Section 2 presents a literature review. Section 3 presents the aim and methodology. Section 4 discusses findings and finally, Section 5 provides conclusions and suggestions for further studies.

2 Literature Review

The stock market is one of the most important components of a country's economy because it contains all economy-related sectors and automatically reflects their impacts on the economy. During crises, the performance of the stock market becomes even more important as it reflects the impact of the crisis on the economy. Stock market indices are an important instrument for investors to understand the overall performance of a particular sector or the entire stock market, [6], indicating that "stock investment provides benefits in the form of dividends as a share of company profits and in the form of capital gains, namely the difference between the selling price of the shares and the buying price of the shares." Investors want to gain more. To do this they monitor the stock prices and changes in the prices of each investment instrument. Stock investment provides huge benefits in the long term, high levels of liquidity investing with small capital, [6].

The banking sector is a significant part of the stock market, and the performance of banks plays a critical role in the overall performance of the market. Most of the financial indexes are composed of banking sectors. For example, the Royal Bank of Canada (RBC), Toronto-Dominion Bank (TD), Bank of Montreal (BMO), and Bank of Nova Scotia (BNS) are in the top 10 constituents of the S&P/TSX Composite Index that is the primary gauge for Canadian-based, Toronto Stock Exchange listed companies in Canada.

The stock market is a very complex and substantial financial system, so various economic and political factors affect the changes in the stock market at every moment, [1]. The stock prices go up and down, it can be difficult to predict how much or when it will go down, [4]. Changes in stock prices are the most important concern to the stockholder in the market, [1]. The stock prices of individual banks are also affected by various market factors, including stock market indices. The study, [4], grouped the main factors that affect stock prices, into four parts, company news and performance, industry performance, investor sentiment, and economic factors. Therefore, accurately predicting the upward and downward trends of stock prices remains a significant challenge for all investors, [7]. Stock prices are formed by the prices of instruments and their percentage amounts in their portfolio, it is an essential issue to learn more about the factors that can affect stock prices. Since banks play an important role in financial systems and their performance has a significant impact on the economy, the stock prices of banks are easily affected during crises. Analyzing the factors that affect the stock prices of banks can help investors better understand how to respond to fluctuations in the market and make informed decisions about investments, risks, and regulations.

In recent years, there has been an increasing interest in the relationship between the daily closing price of banks and various index values during crises. In literature, many scholars studied stock market prices, including the effects of indexes on stock market prices or returns as well as forecasting of stock indexes, [7], [8], [9], [10]. They used various methods such as LR, [2], [3], [11], penalized logistic regression, [7], multiple linear regression (MLR), [1], [10], decision trees (DT), [2], discriminant analysis (DA), [8], Partial linear regression (PLS), [8], data mining (DM), [9], machine learning (ML), [1], [9], and other techniques. One scholar used the LR model with the gradient-boosted decision trees (GBDT) and support vector machine (SVM) aiming to predict and engage in the trading of stock indexes, [9]. Other scholars combined technical analysis with group penalized logistic regressions, and proposed group SCAD/MCP penalized logistic regressions with technical indicators to predict up and down trends for stock prices. This novel prediction method was implemented using three stocks: BAC, Amazon, and Citibank. The objective was to forecast whether the stock prices would rise or fall the following day, [3]. Likewise, LR was employed to investigate the impact of daily trading volume at the Botswana Stock Exchange on daily stock market movement. The findings revealed that only the trading volume from three days prior influenced the current stock market index movement. Interestingly, no significant impact was observed from the trading volumes of the past five days on today's stock market movement, [12].

Another study constructs a global economic policy uncertainty index through the principal component analysis of the economic policy uncertainty indices for twenty primary economies around the world, [13]. The PCA-based economic policy uncertainty index demonstrates a positive correlation with both volatility and correlation in the global financial market. This indicates that higher levels of global economic policy uncertainty lead to increased volatility and stronger correlations among stocks. Comparatively, the PCA-based global economic policy uncertainty index performs slightly better, as it exhibits a more pronounced and significant relationship with market volatility and correlation, [13]. Another research paper integrates the LR model to establish a correlation analysis model between stocks and the Purchasing Managers' Index (PMI), [14]. The study employs PMI data from the National Bureau of Statistics as a sample and conducts experiments to evaluate the effectiveness of the proposed system model. The experimental analysis reveals that the algorithm developed in this paper yields significant results, further confirming the robust correlation between PMI and stocks, [14]. Interestingly, one scholar examines the predictability of the twelve most liquid cryptocurrencies by employing machine learning classification algorithms, such as support vector machines, LR, artificial neural networks, and random forests. The analysis is conducted at both daily and minute-level frequencies. The models utilize historical price data and technical indicators as features to make predictions, [15].

In another research endeavor, the aim is to examine the influence of US financial stress on the risk-return dynamics within the Indian equity market. This investigation employs a combination of Markov regime-switching and binary LR models. The study incorporates the weekly closing local values of benchmark equity indices, namely 'CNX Nifty 50 and S&P 500,' along with the St. Louis Fed Financial Stress Index (SFSI). The findings of the LR model reveal a positive association between US financial stress and the probability of a bear regime being present, [16]. Similarly, another research paper introduces a learning architecture called LR2GBDT for forecasting and trading stock indices. The proposed architecture is evaluated by comparing its performance with several other models, namely LR, GBDT, SVM (support vector machine), NN (neural network), and TPOT (tree-based pipeline optimization tool), [2]. The evaluation is conducted using data from three stock indices belonging to two different stock markets: an emerging market (Shanghai Stock Exchange Composite Index) and a mature stock market (Nasdaq Composite Index and S&P 500 Composite Stock Price Index). Under the same test conditions, the cascaded LR2GBDT model not only outperforms the other models but also demonstrates statistically and economically significant improvements in exploiting simple trading strategies, even when considering transaction costs, [2].

Financial ratios play a crucial role in shaping investors' expectations of stock prices and consequently influence their investment decision-making process, [17]. These ratios are utilized by analysts, investors, and researchers to forecast future trends in stock prices. Ratio analysis has become a vital tool for fund managers and investors to assess the intrinsic value of shares, making financial ratios extensively employed for stock valuation. In the existing literature, a specific paper aims to predict the performance of stocks using Multinomial Logistic Regression (MLR), [17]. The paper employs financial ratios as practical selection criteria to categorize stocks into three groups: GOOD, AVERAGE, and POOR, based on their returns and variances compared to the market's returns and variances. The primary objective of this paper is to explore the applicability of these financial ratios for predicting stock market returns within the Indian market context, [17].

In another research paper, the focus is on analyzing the determinants of debenture issuing prices in Brazil between the years 2000 and 2004. A factor model is employed, wherein exogenous variables are used to explain the behavior of returns and prices. The variables examined in this study encompass rating, index selection, maturity, country risk, basic interest rate, spread between long-term and short-term rates, stock market index, and foreign exchange rate. The findings reveal that the choice of index, probability of default, and bond maturity significantly influence pricing. Moreover, the study highlights a correlation between long-term bonds and higher-rated issuances, [18]. In addition, a researcher investigates the structural dynamics of the Egyptian stock market after the implementation of the economic reform program in 1991, employing LR analysis. The findings from the LR reveal noteworthy alterations in market activity, market size, market liquidity, and market concentration data, [19]. In another research paper, the authors employ an LR approach to examine the relationship between market conditions in Croatia and the classification problem of market inefficiency, [20].

They analyze the daily returns of CROBEX, spanning from September 1997 to July 2021, to assess the market efficiency of the Croatian stock market. Based on empirical findings, the study reveals the time-varying nature of the stock market, with price levels and trading volumes emerging as significant indicators of market efficiency, [20]. Specifically, periods characterized by lower prices and higher liquidity were more likely to exhibit inefficiency, potentially indicating trading opportunities within the Croatian stock market, [20].

Machine learning is another forecasting method, especially when variables in the model are nonstationary and weak relationship among the variables, [9]. A researcher undertakes a comparative analysis of three predictive models, namely Support Vector Machine (SVM), Long Short-Term Memory Recurrent Neural Network (RNN), and LR, to forecast the direction of price movement. The study employs data comprising the share codes from the VN30 list between January 1, 2015, and January 27, 2022, with daily trading activities considered. The "rolling window" approach is utilized, resulting in the RNN model achieving an average forecast accuracy of 82.19%. Additionally, LR is found to play a crucial role in determining the statistical significance of input variables. Based on the experimental results, the study recommends the adoption of machine learning algorithms to enhance prediction accuracy. Simultaneously, investors are advised to consider company-specific characteristics when formulating medium and long-term investment plans, [9].

Likewise, in another research investigation, the study examines various linear classification models, including LR classification (LR), linear discriminant analysis (LDA), partial least-squares discriminant analysis (PLS-DA), penalized discriminant analysis (PDA), and nearest shrunken discriminant analysis, [8]. The objective is to compare their performance in predicting the stock market prices of the top six banks in Bangladesh. The results indicate that PDA performs well in the presence of multicollinearity or the risk of overfitting. LDA yields better approximations when the data exhibit multivariate normality, while the nearest shrunken method is effective when dealing with high-dimensional data. Interestingly, despite the data in this study possessing all the aforementioned characteristics, LR demonstrates a lower misclassification rate or apparent error rate. Consequently, the study suggests that if there are predictors with high correlation, multicollinearity, multivariate normality, and high dimensionality, LR should be preferred among the linear classification models, [8]. In a similar vein, another study focuses on predicting the stock price movement on the second day following the release of companies' annual reports, utilizing a range of models such as decision trees, LR, random forest, neural networks, and prototypical networks. The experiments are conducted using two sets of financial indicators sourced from the East Money website, which are disclosed by the companies. However, the results indicate that these models do not exhibit strong predictive capabilities for determining stock price tendencies. Additionally, after applying filters to include only stocks with a return on equity (ROE) greater than 0.15 and a net cash ratio greater than 0.9, it is observed that the predictability of stock price movements on the second day after disclosure remains weak. The random forest classifier achieves the highest accuracy of approximately 59.6% and a maximum precision of about 0.56 on the test set, but overall performance remains limited. Furthermore, the study finds that stock filtering does not enhance the predictive performance significantly. Overall, random forests demonstrate the best performance among the models considered, which aligns with previous research findings, [21].

A different study suggests a novel approach to creating volatility networks for global stock markets. This involves constructing both undirected and directed networks by analyzing the pair-wise correlation and system-wide connectedness of national stock indices using a vector auto-regressive model, [22]. The researchers investigate the impact and utility of network indicators by employing them as inputs for various machine learning techniques, such as LR, support vector machine, and random forest, [22]. Within this framework, two strategies are devised: a global stock market prediction strategy and a regional allocation strategy targeting developed and emerging markets, [22]. The results indicate that network indicators serve as valuable supplementary tools for predicting the global stock market and determining the relative directions (up or down) of regional markets, [22].

Aiming to provide a comprehensive understanding of the factors that affect the stock prices of banks to help investors and financial institutions during crisis periods, this study examines how the index values affect the closing prices of five major banks in Canada during five crisis periods using the LR method.

3 Aim and Methodology

The banking sector is a significant part of the stock market, and the performance of banks plays a critical role in the overall performance of the market. The corresponding index values in the stock market play a significant role in determining the daily closing prices of banks, especially during crisis periods, indexes in the stock market fluctuate and directly affect the stock prices of banks.

This paper aims to investigate the impact of various price indexes on the daily closing prices of banks during the crisis periods. Additionally, the study aims to identify any discernible patterns in the influence of indexes on daily stock market prices during times of uncertainty.

To achieve this objective, data on the daily common stock market prices and indexes of five major Canadian banks (BMO, BNS, CIBC, RBC, and TD) were collected. The data covered the period from January 1, 1975, to December 31, 2020. The data of five banks were obtained from the source, [23], [24]. The study considered the daily closing price (DCP) of stocks as the dependent variable. The independent variables comprised fifteen out of the total twenty-nine indexes, specifically the daily price indexes (DPI) represented by ind1 to ind29. Among these,

Table 1. Price index definitions

Index Code	Definition
ind1	S&P/TSX Composite DPI
ind3	Sector 10 (Energy) DPI
ind5	Sector 15 (Materials) DPI
ind7	Sector 20 (Industrials) DPI
ind9	Sector 25 (Consumer Discretionary) DPI
ind11	Sector 30 (Consumer Staples) DPI
ind13	Sector 35 (Healthcare) DPI
ind15	Sector 40 (Financials) DPI
ind17	Sector 45 (Information Technology) DPI
ind19	Sector 50 (Telecommunications Services) DPI
ind21	Sector 55 (Utilities) DPI
ind23	S&P/TSX 60 DPI
ind25	S&P/TSX Mid Cap DPI
ind27	S&P/TSX Small Cap DPI
ind29	S&P/TSX Venture DPI
ind31	Call Loan Interest Rate
ind32	Daily Foreign Exchange Rate
ind33	CFMRC (DEWI)
ind34	CFMRC Daily (VWI)
ind35	CFMRC (DEWI) Under $2
ind36	CFMRC (VWI) Under $2
ind37	CFMRC (DEWI) Over $2
ind38	CFMRC (VWI) Over $2

CFMRC: Canadian Financial Markets Research Center; S&P/ TSX: Standard and Poor (stock performance)/Toronto Stock Exchange; DPI: daily price index; DEWI: daily equal-weighted index; VWI: value-weighted index. Source, [23], [24].

the odd-numbered indexes represented daily price indexes, while the even-numbered indexes represented daily return indexes. However, the study excluded the return indexes due to their high correlation with the closing price variable. Of the remaining indexes, three (ind33, ind35, and ind37) were daily equal-weighted indexes (DEWI), three (ind34, ind36, and ind38) were value-weighted indexes (VWI), ind31 represented the call loan interest rate, and ind32 represented the daily foreign exchange rate. It is worth noting that certain indexes had different starting time points. Indexes 3-22 covered the period from January 1, 1975, to December 30, 1987, while indexes 23-30 spanned from January 1, 1975, to May 31, 2002, [24]. Any missing periods within each index were excluded from the analysis, specifically if they occurred during the crisis periods under investigation. The model employed the independent variables as listed in Table 1, [24].

Fig. 1: Daily closing prices of five banks from January 1, 1975, to December 31, 2020, [24].

To identify periods of crisis, a graph was constructed, representing the daily closing prices of each bank (Figure 1). The graph was then analyzed by referring to documented Canadian economic crises and focusing on shared periods of decline. Five distinct crisis periods were identified as follows:

- CR I (Crisis Period I): January 1, 1992, to April 30, 1993.
- CR II (Crisis Period II): July 1, 1998, to October 30, 1998.
- CR III (Crisis Period III): May 1, 2007, to March 30, 2009.
- CR IV (Crisis Period IV): September 1, 2014, to February 29, 2016.
- CR V (Crisis Period V): February 1, 2020, to March 30, 2020.

These crisis periods were determined based on specific time intervals during which significant financial disruptions or instability occurred, [24], and using the declining periods of DCPs in Figure 1. While daily price indexes typically derive from DCPs within the Toronto Stock Market, this paper adopts a unique approach by examining price indexes in the reverse direction to search for a significant impact on DCP in different crisis periods and also the price index differences among the crisis periods in conjunction with the recession or depression.

In this paper, to determine the most important price indexes that affect the daily stock closing price of the banks in Canada, the five largest banks' secondary data were analyzed by logistic regression analysis using SPSS software and Excel.

LR is a statistical method that is used to analyze relationships between a set of independent variables and a binary (categorical) dependent (response) variable. The study, [12], indicated that “a LR model become a popular model because of its ability to predict, classify and draw relationships between a dichotomous independent variable and dependent variables'. The main difference between LR and Multiple Linear Regression (MLR) is the type of dependent (response) variable and the outcome and the normality conditions. MLR and LR requirements on the dependent variable are different. While MLR works with the continuous dependent variable, LR works with the binary dependent variable. For MLR, all variables, either dependent or independent variables, should be normally distributed and the residues must have the same variance. However, for LR, there is no requirement for the dependent and independent variables to be normally distributed and the residues to have the same variance. LR is modeling the probability of outcome occurring based on the values of the independent variables, [17], [25]. LR results provide a classification table in the output, [25]. This 2×2 classification table presents the observed values on the outcome and predicted values for the outcome and it will show the accuracy of the LR model in percent, [25]. The LR model uses the logistic function to map the linear combination of the independent variables to the range of [0, 1]. The logistic function is defined as:

$$P(Y=1|X)=\frac{1}{1-e^{-z}} \tag{1}$$

where $P(Y=1|X)$ represents the probability of the dependent variable being 1 given the values of the independent variables X and z is the linear combination of the independent variables and their coefficients:

$$z=\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n \tag{2}$$

In the equation above, β_0 represents the intercept, $\beta_0,\beta_1,\beta_2,\cdots,\beta_n$ are the coefficients corresponding to the independent variables $X_1,X_2,\cdots,X_n$, respectively, [20].

In LR, to estimate the coefficients the maximum likelihood estimation (MLE) method is commonly used, [20]. The MLE aims to find the values of $\beta_0,\beta_1,\beta_2,\cdots,\beta_n$ that maximize the likelihood of observing the given data. This involves minimizing the log-likelihood function:

$$logL(\beta)=\sum[y_i * log\big(P(Y=1|X_i)\big)+(1-y_i) * \log(1-P(Y=1|X_i))]\log \mathrm{L}(\beta) = \sum[y_i * \log(\mathrm{P}(\mathrm{Y}=1|X_i)) + (1-y_i) * \log(1-\mathrm{P}(\mathrm{Y}=1|X_i))] \tag{3}$$

where i ranges from 1 to the total number of observations, y_i is the observed outcome for the ith observation, and $P(Y=1|X_i)$ is the predicted probability of the dependent variable being 1 given the values of the independent variables in the ith observation, [19]. Once the coefficients are estimated, they can be used to predict the probability of the dependent variable being 1 for new observations based on the values of the independent variables. In summary, LR utilizes the logistic function to model the relationship between a binary dependent variable and independent variables. By estimating the coefficients using the maximum likelihood estimation method, LR allows us to predict the probability of the dependent variable's outcome based on the independent variables' values. In summary, multiple linear regression predicts continuous numerical outcomes, while LR predicts probabilities or classifies binary outcomes, [20]. LR analysis is often used to investigate the relationship between discrete responses and a set of explanatory variables. LR uses logit as a link function, i.e., it takes the log of the odds of the success ratio, [19].

To facilitate LR analysis, the DCP (z) was transformed into binary format, distinguishing positive differences between the current DCP and the previous day's DCP as "P" which is encoded as “1” and negative differences as "N" which is encoded as “0”. Hence, the dependent variable, z, is defined in the following manner

$$DCP=z=\begin{cases}1, & if\ DCP\ increased\\ 0, & if\ DCP\ dicreased\end{cases} \tag{4}$$

$$\mathrm{DCP} = z = \beta_0 + \beta_1 \mathrm{ind1} + \beta_2 \mathrm{ind3} + \beta_3 \mathrm{ind5} + \beta_4 \mathrm{ind7} + \beta_5 \mathrm{ind9} + \beta_6 \mathrm{ind11} + \beta_7 \mathrm{ind13} + \beta_8 \mathrm{ind15} + \beta_9 \mathrm{ind17} + \beta_{10} \mathrm{ind19} + \beta_{11} \mathrm{ind21} + \beta_{12} \mathrm{ind23} + \beta_{13} \mathrm{ind25} + \beta_{14} \mathrm{ind27} + \beta_{15} \mathrm{ind29} + \beta_{16} \mathrm{ind31} + \beta_{17} \mathrm{ind32} + \beta_{18} \mathrm{ind33} + \beta_{19} \mathrm{ind34} + \beta_{20} \mathrm{ind35} + \beta_{21} \mathrm{ind36} + \beta_{22} \mathrm{ind37} + \beta_{23} \mathrm{ind38} \quad (5)$$

where, $\beta_i, (i = 0, 1, 2, \dots, 23)$ are the Impact values of indexes.

After conducting the analysis in SPSS, the following statistical measures were utilized to assess the LR models: the Pearson chi-square test, -2 log-likelihood, the significance of the Hosmer-Lemeshow test, and the Cox & Snell R-square and Nagelkerke R-square. The results will be discussed in the following section.

For LR models, to assess the goodness of fit, the Pearson Chi-square test is commonly used. It tests whether the LR model fits the data well or not under the following hypotheses:

Ho: The LR model fits the data well

Ha: The LR model does not fit the data well.

The test statistic measures if there is a significant difference between the observed and expected frequencies of the binary dependent variable and evaluates the overall goodness of fit of the LR model, [17]. If the p-value is less than the significant level, it is concluded that there is evidence to believe that the LR model does not fit the model well. Conversely, if the p-value is greater than the significance level, it is concluded that there is insufficient evidence to believe that the LR model does not fit the data well, [17].

The -2 log-likelihood is another measure for LR models, which assesses the overall goodness of fit of the LR model. It measures the difference between the observed data and the predicted probabilities from the LR model, [17]. The lower -2 log-likelihood value indicates that the LR model predicts the outcomes with higher probability,

The Hosmer-Lemeshow test is another test to test whether the model fits the data well. Similar to the Pearson Chi-square test, it tests the model under the following hypotheses:

Ho: The LR model fits the data well

Ha: The LR model does not fit the data well.

If the p-value is less than the significant level, it is concluded that there is evidence to believe that the LR model does not fit the model well. Conversely, if the p-value is greater than the significance level, it is concluded that there is insufficient evidence to believe that the LR model does not fit the data well, [26], [27].

The Cox & Snell R-square is the other measure that measures the proportion of the total variation in the binary dependent variable that is explained by the LR model. Its value changes from 0 to 1, [28], [29]. Interpretation of it is similar to the R-square in MLR, but LR R-squared values are typically lower than those of linear regression due to the nonlinear nature of the LR model, [28], [29]. When the value of Cox & Snell R-square is zero, it is concluded that the model explains none of the variation. On the other hand, when it is 1, it is concluded that the model explains all of the variation, [28], [29].

The last measure that is used in this paper is the Nagelkerke R-squared which is also known as the Cox & Snell R-squared. The Nagelkerke R-squared provides an estimate of the proportion of the variation in the binary dependent variable that is explained by the LR model, [29].

4 Finding and Discussion

In this section, to explore which indexes had a positive or negative impact on the DCP of five major banks in Canada during the five crisis periods LR results are discussed in detail after giving the characteristics of the crisis period.

4.1 CR I: Crisis I (1/1992-4/1993)

Canada experienced economic crises and recession in the early 1990s, then it turned to economic recession in CR I, [30], [31]. During this crisis, the Canadian economy significantly declined. While the real GDP decreased by more than 1 percent, the unemployment rate increased by more than 10 percent, [31]. Many industries were affected dramatically, and many people lost their jobs. Canada also experienced an exchange rate crisis during this time, [30], [31]. The value of the Canadian dollar depreciated significantly, leading to concerns about its stability and impact on trade and investment.

Table 2. Logistic regression results of five banks during Crisis I (1/1992-4/1993)

CR I (1/1992-4/1993)										
	BMO	Exp(B)	BNS	Exp(B)	CIBC	Exp(B)	RBC	Exp(B)	TD	Exp(B)
Constant	0.317***	1.423	19.19**	207506113.8	-0.021***	0.979	0.361***	1.435	2.3**	10.448
ind9			-0.009***	0.902						
ind31									-0.385**	0.68
ind34	-35765.03***	0.0000			408.2**	1.097E+177				
ind36	81.35**	2.356E+35								
ind38	1716.594*	2.00E+02	209.23*	6.036E-120			259.527*	5.14E+112	188.206*	3.068E+81
-2 loglikelihood	148.430ᵃ		138.113ᵃ		125.757ᵇ		146.181ᵃ		142.946ᵃ	
Hosmer and Lemeshow Test sig.	0.466		0.076		0.782		0.882		0.78	
Cox & Snell R Square	0.153		0.208		0.384		0.177		0.171	
Nagelkerke R Square	0.182		0.279		0.489		0.241		0.233	

**p<0.001, **p<0.05, ***p>0.05, a: Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001, b: Estimation terminated at iteration number 7 because parameter estimates changed by less than 0.001, c: Estimation* *terminated at iteration number 5 because parameter estimates changed by less than 0.001*

Table 2 depicts the LR analysis results of five banks for CR I (1/1992-4/1993). The LR results for the CR I (1/1992-4/1993) dataset indicate the associations between the independent variables (ind9Sector25-Consumer Discretionary Daily Price Index, ind31-Call Loan Interest Rate, ind34CFMRC-Daily Value Weighted Index, ind36CFMRC-Value Weighted Under $2 Index, and ind38CFMRC-Value Weighted Over $2 Index) and the dependent variables (DCPs of BMO, BNS, CIBC, RBC, TD). The analysis includes the coefficients, exponential values (Exp(B)), and statistical significance levels. ind1SPTSX, ind3, ind5, ind7, ind11, ind13, ind15, ind17, ind19, ind21, ind23, ind25, ind27, ind29, ind32 are not included in any of the models. The LR results are slightly different from the MLR results in another study that used the same data set, [24]. In that study, when they looked at the same data set using MLR, they found that after ind15 (Financials), the most influential factor on the DCP of five banks was ind21 (utilities). Following that were ind3 (Energy), ind7 (Industrials), and ind13 (Health Care) during the CR I. Some of these factors had positive impacts on the banks' DCPs, while others had negative impacts. This happened because each bank used different investment tools with varying percentages in their portfolio, [24]. The differences in LR and MLR results could be due to the type of dependent variable used, continuous for MLR and discrete for LR. The LR results show the coefficients for each independent variable, along with the significance level and the exponentiated coefficient (Exp(B)). The constant term is also included, which represents the intercept of the regression equation. The constant terms in the LR model have coefficients of 0.317, 19.15, -0.021, 0.361, and 2.8 are statistically significant at the $p<0.001$ level for BMO, CIBC, and RBC, and the $p<0.05$ for BNS and TD. This indicates that when all independent variables are zero, there is a significant effect on the log odds of the dependent variable.

Ind9Sector25-Consumer Discretionary Daily Price Index hurts only the DCP of BNS and similarly, the ind31-Call Loan Interest Rate has a negative impact on only the DCP of TD and the ind36CFMRC-Value Weighted Under $2 Index has a negative impact on only DCP of BMO. ind9Sector25-Consumer Discretionary Daily Price Index and ind31-Call Loan Interest Rate are significant at the $p<0.01$ level. However, the ind34CFMRC-Daily Value Weighted Index is included in the LR models of BMO and CIBC. Among the independent variables, ind34CFMRC-Daily Value Weighted Index and ind36CFMRC-Value Weighted Under $2 Index have statistically significant coefficients at the $p<0.05$ level. ind34CFMRC-Daily Value Weighted Index has a negative coefficient of -55565.65, suggesting a negative relationship with the DCP of BMO, and has a positive coefficient of 408.25, suggesting a positive relationship with the DCP of CIBC. Ind36 has a positive coefficient of 81.53, indicating a positive association with the DCP of BMO. Both variables are significant at the $p<0.001$ level. The ind38CFMRC-Value Weighted Over $2 Index is included in all LR models, except for the LR model of CIBC, and is statistically significant at $p<0.001$. The exponential values (Exp(B)) provide the odds ratios associated with each independent variable. For example, the ind34CFMRC-Daily Value Weighted Index has an exponential value of 0.0000, indicating that for a one-unit increase in the ind34CFMRC-Daily Value Weighted Index, the odds of the dependent variable decrease significantly. ind36CFMRC-Value Weighted Under $2 Index has an exponential value of 2.559E+35, indicating a substantial increase in the odds of the dependent variable with a one-unit increase in ind36CFMRC-Value Weighted Under $2 index.

The -2 loglikelihood values for each dependent variable provide information about the goodness of fit of the model, [25]. Lower values indicate a better fit, [25]. The values range from 125.757 to 142.046, suggesting that the model fits relatively well for these dependent variables. The Hosmer and Lemeshow Test is used to assess the goodness of fit of the model by comparing the observed and expected frequencies, and its significance levels indicate whether the model fits the data well, [26], [27]. The provided significance levels for BMO, BNS, CIBC, RBC, and TD are greater than 0.05, suggesting that the model fits the data reasonably well. The Cox & Snell R Square and Nagelkerke R Square values provide measures of the proportion of explained variance in the dependent variables, [28], [29]. The values range from 0.133 to 0.409, indicating that the independent variables collectively explain a moderate amount of the variance in the DCP of LR models. Moreover, Omnibus Tests of model coefficients by Chi-square test are all <0.001, therefore overall all models are significant.

In conclusion, the LR analysis suggests that several independent variables have significant associations with the dependent variables in the CR I (1/1992-4/1993) dataset. Ind34, ind36, ind9, ind31, and ind38 are found to have significant effects on the DCP of five banks, as indicated by their coefficients, exponential values, and statistical significance levels.

Table 3 shows the classification results of the LR models. The analysis of the observed and predicted values for the different variables (BMO, BNS, CIBC, RBC, TD) reveals the accuracy of the LR model. The "Percentage Correct" column indicates the proportion of correctly predicted outcomes. Table 3 presents the number of observed instances and the number of predicted instances for each category, as well as the overall percentage of correct predictions. Similarly, for BNS, the model has an overall percentage of 70.6% correct predictions.

Table 3. Classification table[a] for Crisis I (1/1992-4/1993)

Observed		Predicted		Percentage Correct
		N	P	
BMO (step 1)	N	19	28	40.4
	P	9	70	88.6
	Overall Percentage			**70.6**
BNS (step 2)	N	21	26	44.7
	P	11	68	86.1
	Overall Percentage			**70.6**
CIBC (step 1)	N	34	19	64.2
	P	14	59	80.8
	Overall Percentage			**73.8**
RBC (step 1)	N	18	28	39.1
	P	12	67	84.8
	Overall Percentage			**68**
TD (Step 3)	N	39	7	84.8
	P	8	30	78.9
	Overall Percentage			**82.1**

a The cut value is .500; N represents price drop; P represents price up.

For CIBC, the model performs relatively better, with an overall percentage of 73.8% correct predictions. For RBC, the overall percentage of correct prediction is 68%. For TD, the model achieves an overall percentage of 82.1% correct prediction, indicating a good predictive performance. These results suggest that the LR model can reasonably predict the outcomes for the dependent variables in this analysis. The models are applicable to forthcoming crises of a similar nature.

4.2 CR II: Crisis (7/1998-10/1998)

Canada was largely affected by the Asian financial crisis which started in Thailand in mid-1997, then spread to other Asian countries, and turned out to be a global crisis when it spread to the Russian and Brazilian economies, [32]. The Asian financial crisis led to a decline in global investor confidence and increased volatility in international financial markets. As a result of the Asian financial crisis, the Canadian dollar (CAD) experienced significant depreciation against major currencies, including the US dollar. The depreciation of the Canadian dollar had adverse effects on various sectors of the Canadian economy, [32]. The crisis also impacted the Canadian stock market, leading to a sharp decline in stock prices. The Toronto Stock Exchange (TSX) experienced a period of considerable volatility, causing financial stress for investors and companies alike. The financial crisis contributed to an economic contraction in Canada. The decline in export demand, particularly from Asia, along with the stock market turmoil, negatively affected business investment and consumer confidence. Consequently, Canada's GDP growth rate slowed down during this period, [32]. The crisis also affected the Canadian banking sector. Some Canadian banks faced financial strains due to their exposure to the global financial turmoil and their ties to the affected regions. However, the Canadian banking system proved to be resilient, and major banks were able to weather the storm without significant failures or government bailouts, [32].

Table 4 shows the results of a LR analysis with several independent variables (ind7Sector20-Industrials Daily Price Index, ind17Sector45-Information Technology Daily Price Index, ind31-Call Loan Interest Rate, ind32-Daily Foreign Exchange Rate, ind33CFMRC-Daily Equal Weighted Index, ind35CFMRC-Equal Weighted Under $2 Index, and ind38CFMRC-Value Weighted Over $2 Index) and several dependent variables (BMO, BNS, CIBC, RBC, and TD).

Table 4. Logistic regression results of five banks for Crisis II (7/1998-10/1998)

CR II (7/1998-10/1998)	BMO	Exp(B)	BNS	Exp(B)	CIBC	Exp(B)	RBC	Exp(B)	TD	Exp(B)
Constant	-0.197***	0.82	-3.129**	0.044	-0.093***	0.911	-0.36***	1.43	-18.82**	0
ind7			0.023**	1.024						
ind17			-0.032**	0.968						
ind31									2.08**	7.98
ind33									-127.7**	0
ind35			-62.494**	0						
ind38	133.455*	13.258E+57	248.418*	7.858E+107	104.641*	2.786E+45	259.51*	5.142E+112	241.84*	1.068E+105
-2 loglikelihood	73.842[a]		31.936[b]		87.347[b]		140.185[b]		63.351[b]	
Hosmer and Lemeshow Test sig.	0.414		0.598		0.088		0.393		0.549	
Cox & Snell R Square	0.392		0.535		0.289		0.177		0.464	
Nagelkerke R Square	0.525		0.714		0.386		0.241		0.62	

**p<0.001, **p<0.05, ***p>0.05, a: Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001, b: Estimation terminated at iteration number 7 because parameter estimates changed by less than 0.001, c: Estimation* *terminated at iteration number 5 because parameter estimates changed by less than 0.001*

It appears that some of the independent variables, ind7Sector20-Industrials Daily Price Index, ind17Sector45-Information Technology Daily Price Index, ind31-Call Loan Interest Rate, ind32-Daily Foreign Exchange Rate, ind33CFMRC-Daily Equal Weighted Index, ind35CFMRC-Equal Weighted Under $2 Index, and ind38CFMRC-Value Weighted Over $2 Index, have significant effects on some of the dependent variables while the other 17 indexes do not have a significant effect on the DCP of five banks. For example, the ind38CFMRC-Value Weighted Over $2 Index has a significant positive effect on the DCP of BMO, BNS, CIBC, RBC, and TD, as indicated by the positive coefficient and the low p-value. The ind31-Call Loan Interest Rate has a significant positive effect and the ind33CFMRC-Daily Equal Weighted Index has a significant negative effect on the DCP of TD. The ind35CFMRC-Equal Weighted Under $2 Index has a significant negative effect on BNS, as indicated by the negative coefficient and the low p-value. ind7Sector20-Industrials Daily Price Index and has a significant positive effect on the DCP of BNS, however, ind17Sector45-Information Technology Daily Price Index and ind35CFMRC-Equal Weighted Under $2 Index have a significant negative effect on the DCP of BNS. The other variables do not appear to have significant effects on the dependent variables, as indicated by the non-significant p-values. Moreover, Omnibus Tests of Model Coefficients are all <0.001, therefore overall all models are significant. It is interesting that only ind38CFMRC-Value Weighted Over $2 Index is the common index as in crisis I and it has a significant positive effect on all of the DCPs of the five banks during crisis II. These significant coefficients suggest that ind38 has a strong influence on predicting the DCP of five banks.

The p-values for Hosmer and Lemeshow test4th row indicate that the model's fit is statistically significant for all dependent variables except for the DCP of CIBC, [26], [27]. The p-value for CIBC is 0.008, suggesting that the model's fit for CIBC is not statistically significant. Regarding the R-squared measures, [28], [29], Cox & Snell R Square ranges from 0.177 to 0.535, and Nagelkerke R Square ranges from 0.241 to 0.714. These measures indicate the proportion of variance explained by the model, with higher values indicating better model fit. In this analysis, BNS and RBC show relatively higher R-squared values compared to other dependent variables.

In conclusion, the LR results suggest that some independent variables have statistically significant effects on predicting the dependent variables. However, the model's overall fit varies across the dependent variables, with some variables showing statistically significant fits while others do not. The LR analysis demonstrates the significant impact of certain independent variables on the likelihood of specific outcomes represented by the dependent variables. The results highlight the importance of considering these variables when predicting the probabilities of the outcomes of interest.

Table 5 presents the observed and predicted values for the dependent variables (DCP of BMO, BNS, CIBC, RBC, TD) in the LR model the number of observed instances, and the number of predicted instances for each category, as well as the overall percentage of correct predictions during Crisis II. The results are presented for which step of the classification process ends.

Table 5. Classification table[a] for Crisis II (7/1998-10/1998)

Observed		Predicted		Percentage Correct
		N	P	
BMO (step 1)	N	35	11	76.1
	P	10	28	73.7
	Overall Percentage			**75**
BNS (step 4)	N	38	6	86.4
	P	5	35	87.5
	Overall Percentage			**86.9**
CIBC (step 1)	N	34	11	75.6
	P	11	28	71.8
	Overall Percentage			**73.8**
RBC (step 1)	N	18	28	39.1
	P	12	67	84.8
	Overall Percentage			**68**
TD (Step 3)	N	39	7	84.8
	P	8	30	78.9
	Overall Percentage			**82.1**

a: The cut value is .500; N represents price drop; P represents price up.

For BMO, the model achieved an overall percentage of 75%, indicating that it accurately predicted 75% of the outcomes. Similar to BMO, the overall percentage of correct prediction for CIBC was 73.8%. Although the lowest overall percentage of correct prediction was 68% for RBC, it still indicates a satisfactory level of accuracy in predicting outcomes. When compared with BMO, CIBC, and RBC, the overall percentage of correct predictions for TD and BNS were very high, 82.1 and 86.9, respectively. This indicates a relatively high level of accuracy in predicting the outcome for TD and BNS. In conclusion, the LR model demonstrated varying levels of accuracy in predicting the outcomes for different variables. The LR models show promising predictive performance, correctly identifying a substantial proportion of the observed outcomes. These findings suggest that the model has the potential to be a useful tool for predicting the outcomes of interest.

4.3 CR III: Crisis III (5/2007-3/2009)

Canada experienced significant challenges during the economic crisis CR III. This crisis originated in the United States with the collapse of the subprime mortgage market and quickly spread to other parts of the world, [33], [34]. It was the liquidity crisis in the global financial markets, then turned into a solvency crisis, [24]. The financial system in the world is affected dramatically. Mortgage lenders, insurance companies, and commercial as well as investment banks were among those that faced difficulties during this crisis. For example, the big investment bank, Lehman Brothers, precipitated during this crisis. Although Canada's banking sector was generally more conservative and well-regulated compared to other countries, some Canadian banks and financial institutions faced challenges, particularly due to exposure to risky assets and disruptions in global financial markets, [33], [34]. Canada's major banks were able to remain stable throughout the crisis due to lending practices, stricter regulations, and a conservative banking culture. According to, [35], Canada not only through international trade, but also by weakening financial markets, shaking consumer and business confidence, and postponing capital investments, in light of the high level of uncertainty, during this crisis, [24]. The crisis resulted in a significant economic recession in Canada. The country experienced a contraction in economic activity, declining GDP growth, rising unemployment rates, and reduced business investment. Industries such as manufacturing, housing, and automotive were particularly affected, [33], [34].

Table 6 includes coefficients, significance levels, and exponential values for each independent variable included in the LR analysis during the 2007-2009 financial crisis. The coefficients represent the estimated change in the dependent variable for a one-unit change in the corresponding independent variable, while the significance levels indicate the probability that the observed relationship between the independent and dependent variables is due to chance.

Table 6. Logistic regression results of five banks for Crisis III (5/2007-3/2009)

CR III (5/2007-3/2009)										
	BMO	Exp(B)	BNS	Exp(B)	CIBC	Exp(B)	RBC	Exp(B)	TD	Exp(B)
Constant	-0.429*	0.651	-0.247**	0.781	-0.29**	0.748	-0.244**	0.784	-0.236**	0.808
ind33									104.405*	2.3E+45
ind34			4146.226*				2872.365**			
ind35	40.069**	2.5844E+17								
ind36	-74.85*	0	-131.593*	0	-32.952*	0	-109.281*	0	-87.981*	0
ind38	156.12*	1.386E+59	-5987.92*	0	129.347*	1.496E+56	-2647.41**	0	148.881*	4.55E+64
-2 loglikelihood	494.810ᵃ		473.202ᵃ		504.346ᵃ		457.751ᵇ		436.321ᵇ	
Hosmer and Lemeshow Test sig.	0.756		0.055		0.519		0.729		0.478	
Cox & Snell R Square	0.293		0.328		0.282		0.346		0.356	
Nagelkerke R Square	0.382		0.438		0.377		0.463		0.501	

**p<0.001, **p<0.05, ***p>0.05, a: Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001, b: Estimation terminated at iteration number 7 because parameter estimates changed by less than 0.001*

Based on the results in Table 6, it appears that some of the independent variables, ind33CFMRC-Daily Equal Weighted Index, ind34CFMRC-Daily Value Weighted Index, ind35CFMRC-Equal Weighted Under $2 Index, ind36CFMRC-Value Weighted Under $2 Index, ind37CFMRC-Equal Weighted Over $2 Index, ind38CFMRC-Value Weighted Over $2 Index, have a statistically significant relationship with the dependent variable while the other 18 indexes do not have any significance effect on the DCP of five banks. For example, the coefficient for the "ind36CFMRC-Value Weighted Under $2 Index" variable is negative and statistically significant for the DCP of five banks, suggesting that a decrease in this variable is associated with an increase in the dependent variable (which is likely related to financial institution performance during the crisis). On the other hand, while the ind38CFMRC-Value Weighted Over $2 Index has a significant positive effect on the DCP of BMO, CIBC, and TD, statistically significant, it has a significant negative effect on the DCP of BNS and RBC. ind34CFMRC-Daily Value Weighted Index has a significant positive effect on the DCP of both BNS and RBC. This shows that the investments of BNS and RBC are similar during crisis III. ind33CFMRC-Daily Equal Weighted Index and ind35CFMRC-Equal Weighted Under $2 Index have a significant positive effect on the DCP of TD and BMO, respectively.

During Crisis III, there are two common indexes, ind36CFMRC-Value Weighted Under $2 Index and ind38CFMRC-Value Weighted Over $2 Index that affect the DCP of five banks. Similar to Crisis I, in the other study, using the same data with the MLR method, [24], different indexes have an impact on the DCP of banks. In that study, ind15-Financials that have a positive impact on the DCP of all banks, ind11-Consumer Staples, ind13-Health Care, ind17 -Information Technology, ind19 - Telecommunications Services and ind32-Daily Foreign Exchange Rate are important indexes to predict the DCP of banks. The differences between LR and MLR results could be due to the way the dependent variable is treated, it's continuous for MLR and discrete for LR.

The -2 loglikelihood values reflect the goodness of fit of the model, with lower values indicating a better fit, [25]. In this case, the -2 loglikelihood values range from 436.321 to 504.306, suggesting that the model adequately captures the relationships between the predictor variables and the outcomes. The Hosmer and Lemeshow test results indicate the goodness of fit of the model. With p-values ranging from 0.055 to 0.919, the model does not significantly deviate from the expected values for the observed and predicted outcomes, [27]. The Cox & Snell R Square and Nagelkerke R Square values provide an estimate of the proportion of variance explained by the model, [28], [29]. These values range from 0.282 to 0.501, indicating that the model explains a moderate amount of the variance in the outcomes, [28], [29].

In conclusion, the logistic LR reveals significant relationships between the independent variables and the dependent variables. The odds ratios provide information on the direction and magnitude of these relationships. The model fits the data well, and the R-squared values suggest that the model explains a meaningful portion of the variance in the dependent variables. These findings indicate that the independent variables considered have an impact on the likelihood of the observed outcomes. Moreover, Omnibus Tests of Model Coefficients are all <0.001, therefore overall all models are significant. All these models can be utilized for addressing similar financial crises in the future.

The observed versus predicted values for the LR model in CR III (5/2007-3/2009) provide insights into the accuracy of the model's predictions (Table 7). For BMO, the model achieved an overall percentage of 73.3, indicating that it accurately predicted 73.3% of the outcomes. Similarly, for BNS, CIBC, RBC, and TD, the overall percentages were 74.6, 72.6, 76.5, and 77.1, respectively.

These results suggest that the LR model performed reasonably well in predicting the outcomes for the variables under consideration. In conclusion, the LR model demonstrated a moderate to good level of accuracy in predicting the outcomes of interest. The overall percentages indicate a relatively high level of correctness in the model's predictions.

Table 7. Classification table[a] for Crisis III (5/2007-3/2009)

Observed		Predicted		Percentage Correct
		N	P	
BMO (step 3)	N	204	61	77
	P	67	148	68.8
	Overall Percentage			**73.3**
BNS (step 3)	N	194	60	76.4
	P	62	165	72.7
	Overall Percentage			**74.6**
CIBC (step 2)	N	200	63	76
	P	69	150	68.5
	Overall Percentage			**72.6**
RBC (step 3)	N	193	57	77.2
	P	55	172	75.8
	Overall Percentage			**76.5**
TD (Step 3)	N	183	60	75.3
	P	49	185	79.1
	Overall Percentage			**77.1**

a The cut value is .500; N represents price drop; P represents price up.

Overall, the LR model demonstrates reasonably accurate predictions for the dependent variables DCP of BMO, BNS, CIBC, RBC, and TD. The percentages of correct predictions range from 72.6% to 77.1%. These findings contribute to a better understanding of the factors influencing the outcomes and can inform decision-making.

4.4 CR IV: Crisis IV (9/2014-2/2016)

The largest decline in the oil price in the world from mid-2014 to early 2016, negatively affected the Canadian economy, [36]. Canada is the world's third-largest exporter of oil after Saudi Arabia and Russia. The bulk of the oil reserves are located in Alberta, [37]. This decline in oil prices had a negative impact on the energy sector and the regions heavily reliant on oil production, such as Alberta, [36], [38]. It led to job losses, reduced investments, and slower economic growth in those areas. During CR IV, while the energy sector and mainly Alberta were negatively affected by CR IV, the other sectors, such as services, and construction showed resilience and contributed to economic growth, [36], [38].

Table 8. Logistic regression results of five banks for Crisis IV (9/2014-2/2016)

CR IV (9/2014-2/2016)										
	BMO	Exp(B)	BNS	Exp(B)	CIBC	Exp(B)	RBC	Exp(B)	TD	Exp(B)
Constant	0.118***	1.125	-12.84**	0	0.033***	1.034	0.104***	1.11	0.240**	1.293
ind7			-0.004**	0.996						
ind15			0.011*	1.01						
ind33									-210.456*	0
ind34	-3485.8*	0	-4287.18*	0			-2312.81*	0		
ind35			46.348**	135E+20						
ind36					-35.704*	0				
ind38	3736.986*	0	4526.940*	0	229.548*	481E+99	2506.612*	0	412.008*	1.387E+178
-2 loglikelihood	332.691[b]		315.425[b]		375.327[b]		374.100[b]		330.612[a]	
Hosmer and Lemeshow Test sig.	0.524		0.000		0.29		0.16		0.238	
Cox & Snell R Square	0.391		0.419		0.318		0.317		0.41	
Nagelkerke R Square	0.521		0.558		0.424		0.423		0.547	

**p<0.001, **p<0.05, ***p>0.05, a: Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001, b: Estimation terminated at iteration number 7 because parameter estimates changed by less than 0.001*

Table 8 presents the LR outcomes for CR IV. The findings indicate variations in the indexes included in the LR models, along with differing impacts on these models. Some indexes positively affect the DCP of banks, while others have a negative effect. The negative coefficient for BNS and the positive coefficient for BMO and RBC for the constant term suggests that these banks had different trends in stock price change during the crisis period. Among the independent variables, the daily equal-weighted index (ind33CFMRC) had a significant negative impact on TD's stock price, indicating that TD's DCP was adversely affected during the crisis period by changes in this index. The daily value-weighted index (ind34CFMRC) had a significant negative impact on the DCP of BMO, BNS, and RBC. In contrast, the value-weighted over the $2 index (ind38CFMRC) had a positive impact on the stock prices of all five banks, indicating that higher values of this index were associated with higher stock prices of banks.

For the DCP of BMO, the only significant variable is the ind34CFMRC-Daily Value Weighted Index and ind38CFMRC-Value Weighted Over $2 Index. However, for the DCP of BNS, the significant variables are the ind7Sector20-Industrials Daily Price Index, ind15Sector40-Financials Daily Price Index, ind34CFMRC-Daily Value Weighted Index, ind35CFMRC-Equal Weighted Under $2 Index and ind38CFMRC-Value Weighted Over $2 Index. This shows that the investments of BNS are different from the others. Overall, the results suggest that during the crisis period of 2014-2016, the DCPs of five banks were significantly affected by different indexes. The impact of these variables varies across different banks. The common index that has a significant effect on the DCP of five banks is the ind38CFMRC-Value Weighted Over $2 Index. While the ind38CFMRC-Value Weighted Over $2 Index has a positive impact on the DCP of BMO, BNS, CIBC, and RBC, it has a negative impact on the DCP of TD.

The -2 log-likelihood values indicate the goodness of fit of the LR models, [25]. Lower values indicate better model fit, [25]. In this case, the -2 log-likelihood values range from 315.425 to 375.327, suggesting a reasonable model fit for the data. The Cox & Snell R Square and Nagelkerke R Square values indicate the proportion of variance explained by the model, [28], [29]. The values range from 0.318 to 0.558, suggesting moderate to substantial explanatory power. Overall, the LR results demonstrate the relationships between the independent variables and the dependent variables in CR IV. The significant effects and odds ratios highlight the importance of certain variables in predicting the outcomes. Moreover, Omnibus Tests of Model Coefficients are all <0.001, therefore overall all models are significant.

The LR analysis for the observed and predicted values of the dependent variables (BMO, BNS, CIBC, RBC, TD) in CR IV (9/2014-2/2016) shows promising results. Table 9 displays the number of observed and predicted values for each variable, along with the overall percentage of correct predictions.

Table 9. Classification table[a] for Crisis IV (9/2014-2/2016)

Observed		Predicted		Percentage Correct
		N	P	
BMO (step 2)	N	139	41	77.2
	P	41	153	78.9
	Overall Percentage			**78.1**
BNS (step 5)	N	144	38	79.1
	P	34	158	82.3
	Overall Percentage			**80.7**
CIBC (step 2)	N	139	47	74.7
	P	46	142	75.5
	Overall Percentage			**75.1**
RBC (step 2)	N	134	46	74.4
	P	40	153	79.3
	Overall Percentage			**76.9**
TD (Step 2)	N	138	41	77.1
	P	35	159	82
	Overall Percentage			**79.6**

a The cut value is .500; N represents price drop; P represents price up.

Table 9 shows that the LR model performs reasonably well in predicting the outcomes. For BMO, the model correctly predicts 78.1% of the cases, indicating a good level of accuracy. Similarly, for BNS, the model achieves an overall percentage of 80.7% correct predictions, suggesting a reliable predictive performance. CIBC achieved an overall percentage of 75.1%. However, it still demonstrates a reasonable level of accuracy in predicting the outcomes for this variable. For RBC, the model performs with an overall percentage of 76.9% correct predictions. Although slightly lower than BNS, it still indicates a satisfactory level of accuracy in predicting the outcomes. Finally, for TD, the model achieves an overall percentage of 79.6% correct predictions, indicating a good predictive performance for this variable. These results suggest that the LR model performed reasonably well in predicting the outcomes for these variables.

4.5 Crisis (2/2020-3/2020) (CR V)

The global economy has a severe disruption during the CR V due to the outbreak of the COVID-19 pandemic, [39], [40]. Antonio Guterres, the Secretary-General of the United Nations, warned on April 1, 2020, stating that the global community was confronting its most dreadful crisis since World War II, [41], [42]. The novel coronavirus, officially named SARS-CoV-2, began spreading rapidly worldwide, including in Canada, leading to a public health emergency. The rapid spread of the virus led to health emergencies and the implementation of strict public health measures, resulting in economic disruptions, increased unemployment rates, and significant market volatility. Industries such as tourism, hospitality, retail, and entertainment were particularly affected, [39], [43]. The crisis had a serious impact on financial markets, including the Toronto Stock Exchange (TSX). Stock prices experienced extreme volatility and sharp declines as investors reacted to the uncertainties surrounding the pandemic and its potential economic impact, [39], [43].

Table 10 displays the LR coefficients and significance levels for the five major Canadian banks (BMO, BNS, CIBC, RBC, and TD) during the crisis period V. The independent variables include daily price indices for different sectors and the equal-weighted and value-weighted indices for stocks with different market caps. For BMO, the only significant independent variable is the daily equal-weighted index (ind33CFMRC), with a positive coefficient of 141.112 and a significance level of 0.009. For BNS, the significant independent variable is the equal-weighted index for stocks over $2 (ind37CFMRC), with a positive coefficient of 277.279 and a significance level of 0.12. For CIBC, there are two significant independent variables, ind36CFMRC-Value Weighted Under $2 Index and ind37CFMRC-Equal Weighted Over $2 Index. While ind37CFMRC-Equal Weighted Over $2 Index has a positive effect on the DCP of CIBC, ind36CFMRC-Value Weighted Under $2 Index has a significant negative effect on the DCP of CIBC.

Table 10. Logistic regression results of five banks for Crisis V (2/2020-3/2020)

CR V (2/2020-3/2020)										
	BMO	Exp(B)	BNS	Exp(B)	CIBC	Exp(B)	RBC	Exp(B)	TD	Exp(B)
Constant	-0.301***	0.74	0.947***	2.578	-0.089***	0.951	0.275***	1.316	-0.821***	0.879
ind33	141.112**	1.023E+61								
ind36					-30.539**	0				
ind37			277.279**	2.610E+120	93.407**	3.911E+40	351.127**	3.108E+152	300.635**	3.609E+130
-2 loglikelihood	29.92[e]		18.270[e]		56.545[e]		17.650[e]		19.825[e]	
Hosmer and Lemeshow Test Sig.	0.646		0.958		0.667		0.952		0.989	
Cox & Snell R Square	0.471		0.644		0.387		0.615		0.585	
Nagelkerke R Square	0.634		0.880		0.517		0.82		[illegible]	

*p<0.001, **p<0.05, ***p>0.05, b: Estimation terminated at iteration number 7 because parameter estimates changed by less than 0.001, d: Estimation terminated at iteration number 8 because parameter estimates changed by less than 0.001, e: Estimation terminated at iteration number 9 because parameter estimates changed by less than 0.001.

For RBC, the significant independent variable is the equal-weighted index for stocks over $2 (ind37CFMRC), with a positive coefficient of 351.127 and a significance level of 0.024, and for TD, ind37CFMRC-Equal Weighted Over $2 Index has a positive effect with the coefficient of 300.635 on the DCP of TD.

Overall, the results suggest that during Crisis V, the DCP of BNS, CIBC, RBC, and TD were positively influenced by ind37CFMRC-Equal Weighted Over $2 Index, while BMO showed a significant positive relationship only with ind33CFMRC-Daily Equal Weighted Index. It seems that the investments and DCP of banks change according to the character of the crisis. While ind38CFMRC-Value Weighted Over $2 Index which has generally a significant effect on the DCP of banks is the common index for the first four crises, during the Crisis V, ind37CFMRC-Equal Weighted Over $2 Index is the common one, except the DCP of BMO.

When comparing the LR results with another study that utilized the MLR method on the same dataset, [24], the indexes that have either positive or negative impact on the DCP of banks are completely different. While the DCP of banks is influenced by certain indices such as ind33CFMRC, ind36CFMRC-Value Weighted Under $2 Index, and ind37CFMRC-Equal Weighted Over $2 Index in LR models, none of these indices are encompassed within the MLR models, [24]. This discrepancy can be attributed to the nature of the dependent variable; it is continuous in MLR, whereas it is discrete in LR.

In terms of model fit, the -2 log-likelihood values indicate the goodness-of-fit of the LR models, [25]. Lower values indicate a better fit, [25]. The -2 log-likelihood values range from 18.270 to 36.545, suggesting that the models provide a reasonably good fit to the data. The Hosmer and Lemeshow test evaluates the goodness-of-fit of the model. The higher p-values (>0.05) for all variables indicate that the models do not show evidence of a lack of fit, [26], [27]. The Hosmer and Lemeshow Test results indicate the goodness of fit of the LR model based on a significance level. In this analysis, all variables have p-values greater than 0.05, indicating that the model fits the data well.

The Cox & Snell R Square and Nagelkerke R Square values provide information about the proportion of variance explained by the model, [28], [29]. The values range from 0.387 to 0.809, indicating that the LR models account for a substantial amount of variability in the outcome variables.

In conclusion, the LR results for CR V suggest that the variables ind33CFMRC-Daily Equal Weighted Index and ind37CFMRC-Equal Weighted Over $2 Index have significant effects on predicting the outcomes for BMO, BNS, CIBC, RBC, and TD. The models show a reasonably good fit to the data, and they explain a considerable amount of variance in the outcome variables. Moreover, Omnibus Tests of Model Coefficients are all <0.001, therefore overall all models are significant.

The analysis of the LR results for CR V (2/2020-3/2020) suggests that the predicted probabilities align quite well with the observed outcomes for the variables BMO, BNS, CIBC, RBC, and TD (Table 11).

For BMO, the LR model achieved an overall percentage of 85.4, indicating that 85.4% of the observed outcomes were correctly predicted by the model. Similarly, for BNS and TD, the models both achieved an overall percentage of 87.8, suggesting a good fit between the predicted probabilities and the observed outcomes. For CIBC, the model's overall percentage was 75.6, indicating a moderate level of accuracy in predicting the outcomes. For RBC, the LR model demonstrated higher accuracy, with an overall percentage of 90.2. The overall percentages suggest that LR models utilizing the CR V variables demonstrate a reasonable predictive capacity for the observed outcomes of BMO, BNS, CIBC, RBC, and TD. The observed and predicted percentages suggest a satisfactory alignment, indicating the potential usefulness of the LR model in predicting the outcomes of interest.

Table 11. Classification table[a] for Crisis V (2/2020-3/2020)

Observed		Predicted		Percentage Correct
		N	P	
BMO (step 1)	N	21	2	91.3
	P	4	14	77.8
	Overall Percentage			**85.4**
BNS (step 1)	N	15	3	83.3
	P	2	21	91.3
	Overall Percentage			**87.8**
CIBC (step 1)	N	16	6	72.7
	P	4	15	78.9
	Overall Percentage			**75.6**
RBC (step 1)	N	17	3	85
	P	1	20	95.2
	Overall Percentage			**90.2**
TD (Step 1)	N	17	4	81
	P	1	19	95
	Overall Percentage			**87.8**

a The cut value is .500; N represents price drop; P represents price up.

5 Conclusion

Financial crises can differ significantly in terms of what causes them and how severe they are. They might lead to significant drops in stock prices and market capitalization, as well as increased volatility and risk, changes in the overall economic situation, the value of currencies, or external factors like the Covid-19 pandemic, [44]. Since financial markets react quickly to unexpected problems, the impact of these crises is usually felt right away in the markets, and these effects can stick around for a long time, [44], [45], [46].

In the stock market, financial institutions and banks play an important role. For example, CAD$4.6 trillion of assets are managed by financial institutions. The banks manage 70% of these assets and 90% of the banking assets are controlled by the top six banks: BOM, BNS, RBC, CIBC, TD, and

DG (Desjardins Group which is an investment bank), [45]. The Five Big Banks whose data used in this work hold over $100 trillion in assets of Canada, and they are all based in Toronto, [45]. Therefore, it is important for investors, policymakers, and financial regulators to understand how banks are affected by crises. With this in mind, the purpose is to explore the main indicators that have either positive or negative impacts on the DCP of banks and to identify patterns during times of crisis. In order to offer valuable insights that can help investors, policymakers, and financial regulators effectively reduce the effects of upcoming crises, in this paper, the data of five major banks in Canada were examined by LR models of banks during five different crisis periods. LR analysis was conducted with the SPSS software. To facilitate the analysis The DCP values converted into binary form, denoted as "P" for an increase in DCP compared to the previous day and "N" for a decrease in DCP compared to the previous day.

All the LR models during the five crisis periods exhibited higher accuracy percentages in the range of 68 to 90.2. It is concluded that these models could be used for other similar crises in the future. It was imperative to note that these crises resulted from a combination of domestic and global factors, encompassing economic downturns, financial market volatility, and external shocks. Each crisis exhibited its own distinct characteristics and exerted unique impacts on the Canadian economy and society. Therefore, conducting separate analyses allowed for a comprehensive understanding of the diverse effects that each crisis had on the variables under investigation.

CR I: 1/1992-4/1993 Crisis

During CR I, the Canadian economy experienced a significant decrease. The real DCP decreased by more than 1 percent and the unemployment rate increased by over 10 percent, [31]. Canadian companies were dealing with the consequences of high inflation and this included a significant decrease in the values of risky investments, the challenge of managing substantial debts, and also the impact of falling global commodity prices, [47]. The dollar experienced significant depreciation, and its impact on trade and investment, [30], [31].

The LR models employed in this study focused on five specific indexes: ind9Sector25-Consumer Discretionary Daily Price Index, ind31-Call Loan Interest Rate, ind34CFMRC-Daily Value Weighted Index, ind36CFMRC-Value Weighted Under $2 Index, and ind38CFMRC-Value Weighted Over $2 Index to explore their impact on the DCP of five banks during crisis periods.

The results revealed that among the 23 indexes assessed, only one of them, the ind38CFMRC-Value Weighted Over $2 Index, demonstrated a highly significant effect on DCPs across all the LR models, except for the LR model of CIBC. This index held substantial statistical significance at the $p < 0.001$ level in the models where it was incorporated. Furthermore, during crisis periods, it is observed distinct characteristics shaped by a combination of domestic and global factors, such as economic downturns, financial market volatility, and external shocks. The findings suggest that during financial crises of type CR I, policymakers, investors, and financial institutions would benefit from focusing their attention and investments on value-weighted indexes exceeding $2 along with other factors like inflation, political news, etc. and these models can be used for similar future crises.

CR II: 7/1998-10/1998 Crisis

Starting in Asia and spreading all over the world, this global crisis dramatically affected economies, including Canada. During this global crisis, CR II, export demand, particularly from Asia, declined due to currency, which affected business investment. The Canadian stock market also experienced a sharp decline in stock prices, resulting in considerable volatility on the Toronto Stock Exchange (TSX) and financial stress for investors, [32]. Therefore, Canada's GDP growth rate slowed down, and the unemployment rate increased during this period, [32]. Regarding the character of the crisis, the banking sector in Canada was impacted by the crisis as well, especially, small banks were faced financial strains due to their ties to the affected regions. However, Canada's major banks, BMO, BNS, CIBC, RBC, and TD, exhibited remarkable resilience and stability during this crisis and they weathered the storm without significant failures due to strong regulations, [33], [48].

Developed LR models for CR II incorporated either one or a pair of the subsequent indexes out of 23 indexes: ind7Sector20-Industrials Daily Price Index, ind17Sector45-Information Technology Daily Price Index, ind31-Call Loan Interest Rate, ind32-Daily Foreign Exchange Rate, ind33CFMRC-Daily Equal Weighted Index, ind35CFMRC-Equal Weighted Under $2 Index, but surprisingly, the index ind38CFMRC-Value Weighted Over $2 Index was a consistent component in all LR models. Similar to the LR outcome of the crisis CR I, the ind38CFMRC-Value Weighted Over $2 Index is a common index and shows a strong significant positive effect on the DCPs of all five banks during Crisis II in predicting the DCPs. The rest of the indexes showed no significant effect on the DCP of these banks.

The findings of LR models provide valuable insights into the influence of specific indexes on the DCP of five banks during the global financial crisis. The conclusions indicate that both investors and banks should exercise caution when selecting investment instruments and consider directing their investments towards value-weighted indexes exceeding $2 in similar crisis scenarios that may arise in the future. Furthermore, these models can be employed during comparable crises to make informed investment decisions.

CR III: 5/2007-3/2009 Crisis

This study revealed that several indexes exhibited a statistically significant relationship with the DCP of the five banks, while the remaining 18 indexes did not show any significant effect on their DCPs. Particularly, ind33CFMRC-Daily Equal Weighted Index, ind34CFMRC-Daily Value Weighted Index, ind35CFMRC-Equal Weighted Under $2 Index, ind36CFMRC-Value Weighted Under $2 Index, ind37CFMRC-Equal Weighted Over $2 Index, and ind38CFMRC-Value Weighted Over $2 Index were found to be significant factors impacting the DCP.

During Crisis III, we identified two common indexes, namely ind36CFMRC-Value Weighted Under $2 Index and ind38CFMRC-Value Weighted Over $2 Index, as key drivers affecting the DCP of all five banks which contributes to the findings of [49]. These indexes displayed a significant impact on the DCP during this crisis period. The character of Crisis III, which spanned from May 2007 to March 2009, was marked by a significant financial crisis known as the global financial crisis or the Great Recession. Originating in the United States with the collapse of the subprime mortgage market, the crisis quickly spread worldwide, leading to a severe credit crunch, financial instability, and a deep economic recession. While Canada's financial system was relatively more stable than some other countries, it still faced substantial challenges during the crisis, [33], [38]. Despite the challenging economic climate, Canada's major banks exhibited remarkable resilience and stability throughout the crisis. This can be attributed to prudent lending practices, stricter regulations, and a conservative banking culture, [33], [34]. Canada experienced a contraction in economic activity, declining GDP growth, rising unemployment rates, and reduced business investment. Industries such as manufacturing, housing, and automotive were particularly affected by the downturn, [33], [34].

Based on the outcomes of LR models, findings provide valuable insights into the relationships between specific indexes and the DCP of banks during Crisis III. The identification of significant indexes can aid financial institutions and investors in understanding and navigating through such challenging economic conditions. In similar future crises, it is advisable for investors and banks to consider investing in value-weighted indexes that have a value exceeding $2 as found in the outcomes of LR models for CR I and CR II.

CR IV: 9/2014-2/2016 Crisis

The LR models encompassed the examination of several indexes, including ind7Sector20-Industrials Daily Price Index, ind15Sector40-Financials Daily Price Index, ind34CFMRC-Daily Value Weighted Index, the daily equal-weighted index (ind33CFMRC), ind35CFMRC-Equal Weighted Under $2 Index, ind36CFMRC-Value Weighted Under $2 Index, and ind38CFMRC-Value Weighted Over $2 Index. Among the 23 indexes assessed, only the ind38CFMRC-Value Weighted Over $2 Index demonstrated a significant impact on the DCP of the five banks. Although one of the indexes listed above was included in the LR models, the common index with a noteworthy effect on the DCP of all five banks was the ind38CFMRC-Value Weighted Over $2 Index. However, it is important to note that the impact of this index varied among the banks. While the ind38CFMRC-Value Weighted Over $2 Index positively influenced the DCP of BMO, BNS, CIBC, and RBC, it had a negative impact on the DCP of TD.

During the period from September 2014 to February 2016, Canada did not experience a specific crisis; however, it faced multiple challenges due to global economic uncertainties, declining oil prices, and regional economic impacts, [36], [38]. Being a significant oil-producing nation, the sharp decline in global oil prices during this period directly affected Canada's energy sector and regions heavily reliant on oil production, such as Alberta, [36], [38]. The repercussions included job losses, reduced investments, and slower economic growth in these areas. Amidst the complex economic landscape, our findings shed light on the influence of specific indexes on the DCP of banks. The significance of the ind38CFMRC-Value Weighted Over $2 Index underscores its relevance in predicting DCP fluctuations during this challenging period. Moreover, the varying impact on different banks highlights the importance of considering individual bank characteristics and strategies when analyzing the effects of market indexes on their performance.

In conclusion, this research contributes valuable insights into the relationships between specific indexes and the DCP of banks during a time of economic challenges in Canada. The findings highlight the role of the ind38CFMRC-Value Weighted Over $2 Index as a common influential factor and emphasize the need for prudent risk management practices for financial institutions, especially in the context of global economic fluctuations. This contributes to the findings in [13], where indexes like the number of circulating stocks, value, and price-earnings ratio do not have a significant effect on the stock price.

CR V: 2/2020-3/2020 Crisis

The LR models focused on three specific indexes, namely ind33CFMRC-Daily Equal Weighted Index, ind36CFMRC-Value Weighted Under $2 Index, and ind37CFMRC-Equal Weighted Over $2 Index, out of the 23 indexes assessed. The results of our LR analysis provided valuable insights into the influence of these indexes on the DCP of five banks during Crisis V.

During Crisis V, which was primarily triggered by the outbreak of the COVID-19 pandemic, the LR analysis yielded insightful results. The DCP of BNS, CIBC, RBC, and TD were positively influenced by the ind37CFMRC-Equal Weighted Over $2 Index, while BMO showed a significant positive relationship only with the ind33CFMRC-Daily Equal Weighted Index. These findings suggest that the investments and DCP of banks were influenced differently based on the character of the crisis. In previous crises, the ind38CFMRC-Value Weighted Over $2 Index was the common index with a generally significant effect on the DCP of banks. However, during crisis V, the ind37CFMRC-Equal Weighted Over $2 Index emerged as the common influential index, except for the DCP of BMO. The LR results for Crisis V further underscore the significance of ind33CFMRC-Daily Equal Weighted Index and ind37CFMRC-Equal Weighted Over $2 Index in predicting the outcomes for BMO, BNS, CIBC, RBC, and TD during this unprecedented crisis period, which contributes the finding in [49]. The CR V was characterized by the rapid spread of the COVID-19 virus, leading to health emergencies and the implementation of strict public health measures. These measures resulted in substantial economic disruptions, increased unemployment rates, and significant market volatility, [39], [43]. This research highlights the importance of equal-weighted indexes exceeding $2 in influencing the DCP of banks during CR V. Since the different indexes have an impact on the DCP of banks during CR V when compared with the other crises CR I -CR IV, the banks need to adapt their investment strategies and risk management approaches depending on the economic environments.

This study has several limitations that need to be acknowledged. Firstly, the analysis focused only on decreasing periods, as indicated in Table 1, which may not fully capture the entire scope of the actual crisis period, potentially limiting the depth of insights gained. Secondly, missing data during certain periods were excluded from the assessments, potentially introducing some bias in the results. Another constraint is the lack of access to information about the specific investment tools used and their respective amounts by the banks. This missing data could have provided valuable context and potentially influenced the findings. In this study, the DCP of banks was utilized as the main variable of interest. However, using daily returns, as commonly employed in existing literature, such as, [11], [14], [15], [17], [20], might offer more comprehensive insights into the dynamics of bank performance during crisis periods.

In conclusion, the study revealed that the DCP of banks depends on the characteristics of crises and investment instruments of banks in their portfolios, [9]. Economic, financial, political, and other factors form the character of crises, [52]. Therefore, each crisis has its unique characteristics and has a different level of impact on the DCP of banks.

For further studies, including different factors such as bank volatiles, inflation rate, open price, daily call changes, and bid price in the data can be useful to get more specific indexes that affect the daily closing prices. Furthermore, using different methods, which are commonly used in literature, such as machine learning, [2], [15], [17], [50], [51], data mining, [2] or structural models can enhance the robustness of the findings. Although no specific pattern was found for crises in this study and in [50], a comparative study may identify a pattern for different crises. That will help investors and banks to manage their investments accordingly for the upcoming crises. In addition, this study can be repeated with return indexes which are commonly used in literature.

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