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MASTER’S THESIS

Financial Distress Prediction in Digital Finance Platforms

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Declaration of Authorship

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Prague, April 25, 2024 Lin Zhang

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Abstract

What factors contribute most to the financial distress of FinTech firms: capital adequacy, operating activities, or profitability? This paper tries to answer this question by using a logistic model and analyzing the accounting-based data of 973 FinTech firms worldwide from 2018 to 2023. The analysis also considers non-financial variables, and the robustness checks are performed using the ordered response model and the Bayesian model averaging method. The results suggest that during crises, the financial distress of FinTech firms is mainly influenced by profitability and operating activities, with capital adequacy playing a less significant role.

JEL Classification	C52, C53, C58, G21, G32, G33, M41
Keywords	FinTech, failure prediction, CAMELS, logistic regression, ordered response model, ROC, rare event, BMA
Title	Financial Distress Prediction in Digital Finance Platforms

Abstrakt

Jaké faktory nejvíce přispívají k finanční tísni FinTech firem: kapitálová přiměřenost, provozní činnosti nebo ziskovost? Tato práce se snaží zodpovědět tuto otázku pomocí logistického modelu a zkoumáním účetních dat 973 FinTech firem z celého světa z let 2018 až 2023. Analýza také bere v úvahu nefinanční proměnné a robustnost je testována pomocí modelu uspořádané odezvy a metody Bayesovského průměrování modelů. Výsledky naznačují, že během krizí je finanční tíseň FinTech firem ovlivněna především ziskovostí a provozními činnostmi, přičemž kapitálová přiměřenost hraje méně významnou roli.

Klasifikace	C52, C53, C58, G21, G32, G33, M41
Klíčová slova	FinTech, predikce selhání, CAMELS, logistická regrese, model uspořádané odezvy, ROC, vzácná událost, BMA
Název práce	Predikce finanční tísně na platformách digitálních financí

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Acronyms

AIC Akaike Information Criterion

AsTo Asset Turnover

AUC Area Under the Curve

BCM Binary Choice Model

BMA Bayesian Model Average

CAR Capital Adequacy Ratio

CFS Cash Flow Statement

CR Current Ratio

FPR False Positive Rate

GM Gross Margin

LR Leverage Ratio

LRI Likelihood Ratio Index

MCMC Markov Chain Monte Carlo

OLS Ordinary Least Squares regression

ORM Ordered Response Models

P2P Peer-to-Peer

PIP Posterior Inclusion Probability

PM Profit Margin

PMP Posterior Model Probability

RoA Return on Assets

ROC Receiver Operating Characteristic curve

RoE Return on Equity

ROSE Random Over-Sampling Examples

RvG Revenue Growth

TPR True Positive Rate

Master's Thesis Proposal

Author:	M.A. Lin Zhang
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Defense Planned:	June 2024

Proposed Topic:
Financial Distress Prediction in Digital Finance Platforms

Motivation:
Digital Finance Platforms, including digital banks, online brokers, and digital retail financing firms, are generally regarded as FinTech (Financial Technology) companies. These emerging financial firms use the internet, mobile phones, and other modern technologies to provide automated services, such as digital credit offerings and online sales of financial products. By operating primarily online, FinTech firms can reduce operating costs associated with physical branch offices and enhance profitability.

Bankruptcy or failure prediction of traditional banks has been extensively studied, especially following the 2008 financial crisis. FinTech firms, such as digital banks operating solely through mobile phones without physical branch offices, represent a new business model with fewer fixed assets and higher profit margins. Despite their growing importance in the financial sector, the default risks and factors contributing to failure in these firms have not been carefully examined, partly because of the lack of bankruptcy cases among newly established FinTech entities.

The recent COVID-19 pandemic, conflict in Ukraine, and high inflation environment have initiated another recession, resulting in substantial market value losses in the financial sector. This economic decline is primarily because of increased interest rates and concerns over credit losses. Consequently, FinTech firms face economic pressure, as providing easy digital credits to attract new online customers could lead to holding lower-quality assets, thus increasing their vulnerability to bankruptcy.

As the business downturn causes uncertainty in the financial industry, it brings the question of how to evaluate the risk of FinTech firms. Given their unique internet-based asset-light business model, traditional failure prediction models using CAMELS-type indicators may not adequately capture the complexities of FinTech operations. Therefore, this paper aims to identify the key factors contributing to the financial distress of FinTech firms and to determine which factor plays a more significant role in predicting their failures, Capital adequacy, Operating activities, or Profitability.

Hypotheses:
1. Hypothesis #1: The capital adequacy ratio is not the most effective indicator for explaining the failure of FinTech firms.

2. Hypothesis #2: Other control variables, such as company size, company age, private ownership, and location in developed countries, do not significantly influence the financial distress of FinTech firms.

3. Hypothesis #3: Logistic models can provide relatively accurate evaluations of the failure risk of FinTech firms.

Methodology:
Accounting-based standard CAMELS indicators and non-financial variables linked to financial distress are analyzed by a cross-sectional multivariate logit model, with binary/discrete dependent variables taking the value of 1 if the firm is in trouble during the evaluating period and 0 otherwise.

The data for the empirical analysis is obtained from S&P Capital One databases. The dataset consists of accounting-based data from annual financial reports of global FinTech companies providing consumer digital credits during the 6-year period of 2018-2023.

The results of the explanatory variables from the years 2018 and 2019, two years before the crisis, represent the baseline model. Financial ratios are divided into 3 main categories: Capital adequacy (Debt Ratio, Current Ratio, Leverage Ratio), Operating Activities (Revenue Growth, Assets Turnover), and Profitability (Return on Assets, Return on Equity, Gross Margin, Profit Margin).

The dependent variable is a binary value that reflects whether the FinTech company exhibited financial distress during the 2-year period of 2020-2021, as determined by the screen filter of the S&P database, with indicators including “Seeking to Sell”, “Bankruptcy”, “Discontinued Operations”, “Auditor Going Concern Doubts”, “Credit Rating Downgrade”, and “Debt Defaults”. Data from the years 2022-2023 is used for the out-of-sample evaluation.

Other variables include size, age, listing on a stock exchange, and location in a developed market, and are investigated as non-financial control variables.

Expected Contribution:
In the stock market, FinTech firms are often treated as high-tech companies rather than traditional banks, and thus they should not be subject to the same regulatory measures as classic banks. The highly restrictive requirements of banking regulation, which primarily focus on solvency and liquidity, may decrease the operational performance and profitability of FinTech companies, making them more likely to get into trouble.

By implementing widely accepted bankruptcy regression models on recent financial data of FinTech companies during the COVID-19 outbreak and economic downturn period, this paper provides a reference for policymakers to understand which factor is more important, capital adequacy or profitability, to help create effective regulations for digital banks.

Outline:
1. Introduction.
2. Literature review
3. Economic background
   3.1 FinTech and digital bank development

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1 Introduction

In his book “The Curse of Cash” (2017), Kenneth Rogoff proposed the transition to a “less-cash society”, an idea that corresponds with the ongoing consideration among several central banks regarding the potential issuance of digital currencies. This shift towards digital currency coincides with the rapid growth of digital finance platforms, also known as financial technology or FinTech. Thanks to the new internet-based asset-light business models, FinTech firms have been able to continually gain market shares from traditional banks all over the world. The existing Basel III Accord regulations focusing mainly on the capital adequacy of traditional banks may not be efficient enough in addressing the unique risks faced by FinTech firms. Given this situation, it is necessary to evaluate the effectiveness of current regulatory frameworks in mitigating financial risks in the fast-changing world of FinTech. Therefore, this paper tries to answer a fundamental question: which factors serve as better indicators for identifying the financial distress of FinTech firms?

The recent economic downturn caused by COVID-19 was the first global financial crisis these newly created FinTech firms have ever experienced. The external impact of the pandemic brought a relatively large number of them into financial distress. This paper uses the most recent firm-level financial data from 2018-2023 to analyze the effects of CAMELS-type variables on the likelihood of distress, arguing that the distress of FinTech firms is influenced more by profitability rather than capital adequacy.

This paper applies a cross-sectional analysis with binary choice regressions, using financial data extracted from annual reports from 2018 to 2021 for baseline estimation and from 2022 to 2023 for out-of-sample forecasting. By examining the financial statuses of FinTech firms for both one and two years preceding the outbreak of the COVID-19 crisis in 2020, the analysis aims to capture extended and comprehensive effects of explanatory variables. Additionally, this approach tries to differentiate between early indicators of financial challenges and those that emerge at a later stage. This paper defines the dummy dependent variable as a firm in financial distress using a customized filter function provided by the S&P database. To avoid selection bias, this paper specifies the rule of economic failure and manually sets the “Distressed FinTech” standard filter using a list of financial distress indicators, such as events of discontinued operations, credit rating downgrade, and debt defaults.

Non-financial firm characteristics and macroeconomic dummy factors, including size, firm age, public listed, and location, are also considered and evaluated.

The empirical results show that the impact of profitability on the financial distress of FinTech firms is greater than that of capital adequacy. FinTech firms demonstrating higher profitability before a crisis are less likely to face financial hardship once a crisis occurs. This paper conducts several robustness checks, including rare event handling, ordered response model analysis, and the Bayesian model averaging (BMA) approach, with the results remaining consistent relative to the baseline estimates.

This paper makes several contributions to the field of bank failure prediction studies by addressing the likelihood of FinTech firms facing financial distress during crises. Unlike previous research, which primarily focused on the survival of commercial banks, this study marks the first attempt to analyze the failure prospects of FinTech firms. Traditionally, research has concentrated on traditional banks due to the abundance of data from the 2008 financial crisis. However, there remains a noticeable gap in the literature regarding the prediction of the survival of digital finance platforms. This paper fills this gap by thoroughly analyzing the failure prediction of FinTech firms.

Secondly, this paper introduces a new evaluation framework comprising three categories inspired by the classification of operating, investing, and financing activities from the Cash Flow Statement (CFS) structure of annual reports. Instead of relying on six types of financial ratios from the traditional CAMELS approach, this framework categorizes indicators into three groups, *Capital Adequacy*, *Operating Activities*, and *Profitability*, to estimate the impacts of firm-level financial ratios on the likelihood of a FinTech firm being in distress.

This paper also provides a reference for policymakers to create effective regulations for digital banks, arguing that the current heavily restricted banking regulations of the Basel Accord may decrease digital financial service firms' operational performance and profitability, thus causing more FinTech firms to get into distress when crises occur. By analyzing the factors contributing to the distress of FinTech firms, this paper provides references that can assist in formulating regulatory changes that fit the specific needs of the FinTech industry.

The subsequent sections of the paper are structured as follows: Chapter 2 provides a review of the relevant literature. Chapter 3 outlines the current development in the FinTech industry. Chapter 4 discusses the data and models used in the analysis. Chapter 5 presents the empirical findings. Chapter 6 examines robustness tests. Finally, Chapter 7 summarizes the conclusions of the study and discusses their policy implications.

2 Literature Review

Traditional banks have already been the subject of extensive research focused on identifying economically significant factors influencing the likelihood of failure, often with the help of CAMELS ratios. However, the rise of digital finance platforms, or FinTech, offering online credit services introduces new risks. As these platforms are closely connected to the financial industry, any trouble they experience could significantly impact the financial system's stability.

The objective of this literature review is to explore the various methodologies and models developed for bankruptcy prediction, with a particular focus on the banking sector. By examining the theoretical framework related to bankruptcy prediction, historical development, and factors influencing bankruptcy, this review provides a comprehensive understanding of the current state of bankruptcy prediction in the financial industry. Furthermore, this section outlines the contribution of this paper to the topic of bank survival by addressing the research question of what factors make FinTech firms more likely to face financial distress. Finally, it presents the hypotheses proposed by this paper.

2.1 Theoretical framework

The development of bankruptcy prediction models has undergone substantial evolution, driven by improvements in financial theory, data availability, and computational techniques. The history of these models dates back to the early 20th century when researchers began using statistical methods to evaluate the financial health of companies based on data extracted from balance sheets and income statements.

The use of financial ratios. In his groundbreaking study, Beaver (1966) explored the effectiveness of financial ratios in predicting business failure of 158 companies across 38 different industries from 1954 to 1964. His research created the foundational framework for the use of quantitative financial analysis in anticipating corporate distress. While Beaver's work emphasized the importance of financial metrics, its reliance solely on financial ratios may overlook other crucial factors contributing to business failures, such as market conditions and industry dynamics.

The development of multivariate models. Among the various bankruptcy prediction models, Altman's (1968) introduction of the Z-score model became one of the most well-known examples. In this first multivariate bankruptcy prediction model, Altman classified 22 financial ratios into five standard categories and applied linear regression to obtain the Z-score, a metric used to distinguish bankruptcies. Over the next two decades, several modifications were made to the original Z-score model, such as the addition of financial variables, consideration of market-based ratios, and inclusion of country-specific data. Despite these advancements, questions arose regarding the applicability and effectiveness of the generalized Z-score model. In a comprehensive review done in 2017, Altman et al. (2017) analyzed these multivariate models and tested their updated Z-score model with data from 31 countries. Although their research suggested that the general Z-score model remains effective for most countries, it may not have fully accounted for potential limitations in certain regions due to differences in regulatory frameworks and market conditions.

The emergence of binary response models. Given the nature of bankruptcy, binary response models appear to be a logical option for predicting bankruptcy. Bongini et al. (2001) evaluated a static binary logit model to identify financial distress while incorporating country effects through dummy variables. Although this approach allows for capturing country-specific details, it may overlook the dynamic nature of financial distress and fail to account for time-dependent variables adequately.

The employment of neural networks and hazard models. López-Iturriaga et al. (2010) developed a nonlinear model using neural networks to analyze the bankruptcy of 192 U.S. banks between 2003 and 2008. Betz et al. (2014) favored simple static binary choice models over hazard models when evaluating 546 European banks' distress with the data from 2000 to 2013, as their objective was to predict failures rather than forecast the timing of distress. This paper follows this idea and selects static logit models over hazard-based approaches.

The analysis of indicators with a longer time horizon. Cole and White (2012) evaluated a set of logistic regression models based on data from multiple years before the crisis. Specifically, their study evaluated the banks that failed in 2009 using independent variables from 2004 to 2008. However, this approach may raise doubts on the reliability of using data from prior years to forecast failures in the following years, given the fast-changing nature of the financial industry.

The utilization of ordered response models. In their studies, Kick and Koetter (2007) and Van et al. (2021) investigated ordered failure events in banking sector and analyzed the factors influencing financial failure and bankruptcy, respectively. While Kick and Koetter examined the factors influencing financial instability within the German banking sector between 1994 and 2004, Van et al. provided valuable insights into the broader understanding of bankruptcy prediction using the generalized ordered logit model, focusing on 139 manufacturing companies. These studies on ordered logistic modeling made significant contributions to this field by offering comprehensive analyses of stress-related events grouped at various levels, while also examining the factors contributing to financial distress.

In summary, logistic or logit models are the most employed models in academic literature. Kočenda and Iwasaki (2022) examined 2120 estimates gathered from studies in the Web of Science database that included variables related to CAMELS proxies, finding that most estimates (1365) were generated through logistic models. Although their research showed that logistic models are widely used for their simplicity and ease of interpretation, it is worth noting that these models may oversimplify the complex relationships involved in financial distress prediction and may not fully capture the underlying dynamics of the banking sector.

Following the methodologies established in these previous studies, this paper uses binary logit analysis as the baseline model to examine the dependent variable of FinTech failures over the 2-year period of 2020-2021, using the independent variables obtained from the 2019 and 2018 models. The objective is to evaluate the relevance and timeliness of financial data in predicting distress within the FinTech sector. Additionally, the ordered logit model is used in the robustness check section to validate the results obtained from the baseline mode.

2.2 Determinants of bankruptcy

This section reviews previous research on the criteria for defining bankruptcy, key factors or explanatory variables in bankruptcy prediction, and the Bayesian model averaging (BMA) approach for parameter selection.

2.2.1 Criteria for defining bankruptcy

Throughout history, only a limited number of distressed banks have ended up filing for bankruptcy, as they usually were either acquired by larger competitors or received assistance from governments. Generally, governments find it challenging to shut down parts of the financial system, even when multiple banks within the country are technically insolvent. Therefore, it is necessary to expand the definition of failure to include all banks that truly experience distress.

As outright bankruptcies have been relatively uncommon, many studies have developed broader indicators of bank failure to cover various forms of distress observed during crisis periods. Demirgüç-Kunt and Detragiache (1998) stated in their research that banks become insolvent when the value of assets is lower than that of liabilities. Cole and White (2012) considered a bank experiencing a "technical failure" if the combined value of its equity and loan loss reserves from its financial report is below 50% of the worth of its nonperforming assets. Thus, the definition of bank failure was based on a specific financial threshold rather than relying solely on the legal declaration of bankruptcy.

Betz et al. (2014) defined bank distress as the situation when a bank fails to pay interest or when it receives a capital injection from the state. Vazquez and Federico (2015) identified bank failure as when banks were downgraded by Moody's to risk class E or E+ or when their Capital Adequacy Ratios (CAR) fell below the regulatory requirement of 8%. Lin and Yang (2016) evaluated bank-level CAMELS variables from 1999 to 2011 and defined a bank as being in financial distress if it ceased operations or suspended its operations temporarily. Chiaramonte and Casu (2017) classified banks as experiencing financial distress if their coverage ratio is negative within twelve months before a merger takes place or if the BankScope database assigned a status of "dissolved" or "in liquidation" to the bank. Schwarz and Pospíšil (2018) analyzed Czech firm-level microdata, considering companies that undergo bankruptcy not only during the study period but also in subsequent periods. These approaches cover different types of instability in the banking sector, but they might not always align with traditional bankruptcy definitions. As a result, differences in defining the dependent variable of failure could influence the findings across studies.

To obtain a less unbalanced sample of healthy and distressed FinTech firms, this paper uses a similar definition of the broadened bank failure derived from a set of financial distress indicators. These indicators represent economic failure rather than strictly legal or *de jure* failure. Using the screen filter function provided by the S&P database, this analysis could identify and filter out distressed FinTech firms by defining specific event indicators, including "Seeking to Sell", "Bankruptcy", "Discontinued Operations", "Auditor Going Concern Doubts", "Credit Rating Downgrade", and "Debt Defaults". By creating a standardized filter or screener on top of the comprehensive database, this approach effectively mitigates potential selection biases in the data collection process.

2.2.2 Key predictive factors in bankruptcy prediction

The CAMELS system, introduced by the U.S. regulators in 1979, evaluates bank conditions based on six key factors: **C**apital adequacy, **A**sset quality, **M**anagement quality, **E**arnings, **L**iquidity, and **S**ensitivity to market risk, which was last added in 1996. Over the past decades, those CAMELS-type ratio variables have been widely used to predict bank failure since their first introduction by Lane et al. (1986), who integrated these variables into their Cox proportional hazards model to predict the failures of 137 banks in the United States from 1979 to 1984.

However, using CAMELS variables to evaluate firm failure has certain limitations. One limitation arises from the possibility that financial ratios might only indicate symptoms rather than underlying causes of a firm's financial distress. Kočenda and Iwasaki (2022) suggested that this challenge is rooted in the fact that lagging indicators of bankruptcy may not consistently serve as reliable predictors of future bankruptcies. Bongini et al. (2001) addressed this concern by examining the study using solely financial information from the year preceding the crisis to mitigate any influence from supervisors' behavior by addressing distress after its occurrence. Arena (2008) suggested that financial ratios should primarily be used to examine the near-term vulnerability of banks as proxies for fundamental attributes. In his study, he argued that for a deeper understanding of longer-term impacts, it is necessary to consider the weaknesses in operational frameworks, including regulatory systems and corporate governance. Cole and Gunther (1995) dealt with the challenge of multicollinearity in the selection of potential explanatory CAMELS ratios by removing highly correlated variables from the dataset.

Based on these previous approaches, this paper focuses on the cross-sectional financial data from the year before the COVID-19 crisis to calculate the CAMELS ratios as the baseline model sample data. After eliminating highly correlated pairs, these independent variables are subsequently used to evaluate the short-term effects of the fundamental firm-level attributes. The underlying assumption is that these fundamental attributes reliably represent unchanging company conditions during the entire crisis period.

Despite the progress made by these prior studies, certain issues still need to be considered. For example, manually excluding highly correlated variables may lead to the omission of potentially relevant information, thereby affecting the comprehensiveness of the analysis. This limitation makes it necessary to introduce the Bayesian Model Average (BMA) approach.

2.2.3 Bayesian Model Averaging (BMA) for parameter selection

Various empirical investigations in bank survival prediction attempt to uncover the factors influencing the likelihood of failure. However, the presence of numerous potential CAMELS explanatory variables and the lack of clear guidance from economic theory regarding variable selection have resulted in model uncertainty. In response to this challenge, the BMA approach offers a robust solution by using the associated Posterior Model Probabilities (PMPs) as weights for selecting variables. Fernandez and Steel (2001) argued that the BMA framework provides a formal statistical basis for parameter estimation.

The BMA method has shown effectiveness across various statistical model classes, including linear regression, generalized linear models, proportional hazard models, and discrete graphical models. Figini (2012) analyzed each of these cases and found that the BMA approach consistently exhibited improvements in predictive performance. In their recent research, Kočenda and Iwasaki (2022) performed a BMA analysis to mitigate the risk of omitted-variable bias. Inspired by the insights from these previous studies, this paper uses the BMA method in the robustness check section to validate the results obtained from the baseline model.

2.3 Empirical studies

Although CAMELS financial ratios have been extensively used in bank failure prediction studies for nearly three decades, their effectiveness remains uncertain. In their recent study, Kočenda and Iwasaki (2022) conducted a meta-analytical review of 450 studies worldwide gathered from Google Scholar, to identify economically significant factors influencing the likelihood of bank failure. However, their findings suggest little to no significant effects of the CAMELS variables on bank survival predictions.

This uncertainty regarding the effectiveness of CAMELS financial ratios highlights the necessity for robust approaches in both data management and model evaluation to ensure accurate predictions in bank failure analysis. Hence, understanding the various methodologies used across studies for handling sample datasets becomes essential. Therefore, this section focuses on scholarly literature addressing the challenges and limitations associated with input data, including outlier treatment and rare event handling. Additionally, it explores the approaches used to evaluate the performance of forecasts generated by different models.

2.3.1 Outlier management

Extreme outliers of explanatory variables may occur due to limitations and inaccuracies in the data source, thus potentially introducing bias into the outcomes. In their study evaluating bank failures, Schwarz and Pospíšil (2018) identified extreme outliers in the variable of investment-cash flow rate and applied winsorization as a corrective measure. This approach involved adjusting the extreme 0.1 percent of the data, ensuring a more balanced and robust dataset. Similarly, Vazquez and Federico (2015) eliminated outliers by filtering out observations at the 0.5 percentile when employing a probit model based on the cross-sectional distribution of bank-level variables from 2004 to 2007.

While winsorization and percentile-based outlier removal are commonly used techniques in financial analysis, they may potentially alter the original data distribution and introduce biases into subsequent analyses. Therefore, although these methods provide initial steps for handling outliers, their implications should be carefully considered. This paper uses the Winsorize function from the R package developed by Signorell et al. (2021) to address extreme outliers, specifically those falling within the top or bottom 0.1 percent range of the CAMELS ratios.

2.3.2 Rare event handling

The observation sample data in bank failure analysis often exhibits a high level of imbalance, characterized by a significantly lower number of firms experiencing bankruptcy compared to those operating normally. This phenomenon, commonly termed the rare event issue, poses a significant challenge in statistical analysis and modeling.

King and Zeng (2001) were among the pioneers to highlight this rare events problem, which refers to the statistical challenge encountered when attempting to accurately predict or model events that occur infrequently or are rare in nature. Williams (2016) further elaborates on the vulnerability of maximum likelihood estimation of the logistic model to small-sample bias, with the degree of bias significantly impacted by the number of cases in the less frequent class.

To address this sample imbalance issue, researchers often employ a method known as under-sampling, where bankruptcy firms are paired with healthy companies of similar size. This approach dates back to Beaver's (1966) pioneering study in failure prediction, where 79 failed firms were matched with 12,000 non-failed companies using a paired-sample design, resulting in 158 observations. Kočenda and Vojtek (2011) used a similar under-sampling method, selecting a comparable number of well-performing samples to match individual clients who defaulted on loans, thus obtaining an artificially balanced dataset for their logistic regression analysis on retail-loan default prediction. While under-sampling mitigates dataset imbalance, it carries the risk of information loss and bias in subsequent analyses.

As methodologies advanced, Lunardon et al. (2014) developed an R package called ROSE to artificially generate balanced samples using various techniques such as over-sampling, under-sampling, and bootstrapping. These techniques are explored further in the methodology chapter, with empirical results discussed in the robustness check section.

2.3.3 Model performance evaluation

The evolution of failure prediction model performance evaluation methodology has undergone significant development over time. Early studies, such as Beaver (1966), introduced the use of contingency tables to evaluate the prediction accuracy regarding Type I (misclassify bad banks or missing signal) and Type II (misclassify good banks or false alarm) errors. His work established a basic framework to evaluate prediction accuracy by tabulating the occurrences of true positive, true negative, false positive, and false negative outcomes. Similarly, Altman (1968) used an accuracy matrix to illustrate the Z-score model's effectiveness in predicting failures. Accuracy matrices offer a more structured approach to assess prediction accuracy by quantifying both correct and incorrect classifications, providing a more comprehensive understanding of model performance compared to contingency tables.

Three decades later, while Demirgüç-Kunt and Detragiache (1998) still relied on the Akaike information criterion (AIC) to examine the performance of their multivariate logit model in predicting bank crises across 45 countries during 1980-1994, Cole and Gunther (1998) enhanced the evaluation methodology by considering the trade-off between Type I and Type II errors. Their study used a probit model to analyze the impact of CAMELS variables on 12,198 banks in the United States from 1987 to 1990. Hamdaoui (2016) emphasized the importance of selecting the optimal threshold level for interpreting the signals of a crisis in his study on evaluating systemic banking crises through a multinomial logit model. He reasoned that Type I errors hold greater significance than Type II errors because of their potentially higher costs from a welfare perspective. Consequently, he proposed a relatively low probability threshold level of 10% that prioritizes the avoidance of Type I errors.

Fawcett (2006) recommended using ROC curves and the Area Under the ROC Curve (AUC) as a method for evaluating classification models, as this approach offers a robust means of assessing model performance without the need for subjective threshold selection. Likewise, Kočenda and Vojtek (2011) used ROC curves and AUC analysis to compare the quality of models in evaluating the key factors influencing consumer default behavior in retail banking. Following this approach, this paper employs the ROC and AUC methodology in the forecast evaluation section to review model performance.

2.4 Hypotheses development

While existing studies have extensively explored failure prediction in traditional industries, research on the bankruptcy likelihood of FinTech firms remains limited, mainly due to the industry's new emergence and lack of a complete business cycle experience. This research gap presents a unique opportunity to investigate the factors influencing the financial stability of FinTech companies.

Within the limited research on the FinTech sector, the majority of studies primarily concentrate on macroeconomic analyses at the country level. For example, Hodula (2023) examined the impact of FinTech development on bank interest margins across 91 countries from 2013 to 2019. Similarly, Elekdag et al. (2024) applied the volume of FinTech transactions as a factor in their adapted natural logarithm Z-score model to evaluate FinTech's effect on the risk-taking behavior of financial institutions across 57 countries. Specifically, an instrumental variable in their 2SLS estimation process was mobile phone subscription data, serving as a proxy for internet penetration, which is correlated with FinTech transactions.

The recent crises triggered by the COVID-19 pandemic and the conflict in Ukraine have significantly impacted the global economy, providing a timely opportunity to investigate the vulnerabilities of FinTech firms when facing external shocks. Rather than developing a new failure prediction model, this paper seeks to explore the characteristics of the emerging FinTech industry using established methodologies. By using firm-level data and recognized failure prediction techniques such as the binary logistics model, probit model, ordered response model, and BMA approach, this analysis aims to identify the key indicators that predict financial distress in FinTech firms. The central question addressed in this paper is: *Which indicators are most important in predicting the financial distress of FinTech firms: capital adequacy, operating activities, or profitability?*

To achieve this goal, this paper creates a new analysis approach called the CFS framework, which further categorizes the CAMELS ratios into three subgroups: financing, represented by *Capital Adequacy*; operating, indicated by *Operating*

Activities; and investing, reflected by *Profitability*. This analysis proposes three hypotheses.

Hypothesis #1: The capital adequacy ratio is not the most effective indicator for explaining the failure of FinTech firms.

To verify this hypothesis, this paper compares the impact significance of financial ratios from three groups: *Capital Adequacy*, *Operating Activities*, and *Profitability*. This comparison helps determine whether factors related to operating activities or profitability have a greater influence on the failures of FinTech firms than capital adequacy.

Hypothesis #2: Other control variables, such as company size, company age, private ownership, and location in developed countries, do not significantly influence the financial distress of FinTech firms.

In addition to financial metrics, this paper also examines non-financial variables to evaluate their impact on the likelihood of FinTech firms experiencing financial distress.

Hypothesis #3: Logistic models can provide relatively accurate evaluations of the failure risk of FinTech firms.

This hypothesis is tested using ROC curves for performance evaluation. By examining the significant impact of CAMELS-type variables in predicting the financial distress of FinTech firms, this paper aims to offer valuable insights for policymakers.

3 Economic Background

3.1 Evolution of the FinTech industry

FinTech generally refers to the application of new digital technologies in financial services to enhance their accessibility and delivery to customers (Omarova, 2020). Since the 1950s, financial institutions have been applying information technology for payments and transactions, pioneering innovations such as credit cards, automated teller machines (ATM), and electronic stock exchanges. The dot-com bubble of the late 1990s opened doors for early FinTech innovations, including the introduction of online brokerage services and digital wallets.

In the early 2000s, the rise of PayPal signaled the entry of technology companies into the financial services sector, introducing digital assets that changed the operation of modern financial markets. The term "FinTech" became popular alongside the growth of Peer-to-Peer (P2P) lending platforms and mobile payment solutions. Today, with the emergence of FinTech lending which offers consumer digital credits without requiring formal collateral, FinTech is fundamentally changing the landscape of the existing financial infrastructure traditionally dominated by commercial banking.

3.1.1 FinTech categories

In this paper, FinTech represents all types of financial services related to internet banking and digital finance. There exist several types of FinTech firms, each with its own specific focuses and business models.

The first category mainly concentrates on applying transactions and marketplace lending as an agent, as seen in the simple Peer-to-Peer lending model. In such models, borrowers and lenders are directly matched, placing the risk primarily onto the lenders rather than the FinTech platform itself. Additionally, some P2P platforms only refer loan applications to partner banks (Elekdag et al., 2024). Consequently, the risk of financial loss in the event of loan default rests with the partner bank rather than the platform itself.

The second type represents FinTech platforms that use their own financial resources to facilitate transactions between borrowers and lenders, a practice known as balance sheet lending. This category also includes major technology companies that participate in credit and lending activities, a group referred to as “Big Techs” by Cornelli et al. (2023). Additionally, some e-commerce platforms provide credit services to merchants operating within their ecosystems. For example, Amazon Lending offers loans to merchants selling products on Amazon’s platform. In the United States market, an increasing number of FinTech players, including Apple, Google, and other technology giants, are entering financial services. These Big Tech firms are not only offering payment and transaction services but also providing credit cards and digital currencies, resembling a comprehensive retail banking provider.

The third type of FinTech firms comprises digital banks, also known as online banks or neobanks, which primarily operate through mobile phones or the internet. These banks offer a range of financial services, including savings accounts, payment processing, loans, and investments, all accessible through their mobile applications or online platforms. Air Bank, N26, and Monzo are prime examples of digital banks that have gained significant traction in recent years. Based in the Czech Republic, Air Bank offers a range of banking services through its mobile application, with a focus on principles of simplicity and transparency. Headquartered in Germany, N26 has risen as a leading digital bank in Europe, renowned for its customizable savings goals and innovative payment solutions. Monzo, a UK-based digital bank, is known for its innovative features such as instant spending notifications and fee-free foreign transactions.

This paper mainly discusses the second and third types of FinTech firms, which offer consumer credit and hold part of the loans on their own balance sheets. As a result, the bankruptcy or financial distress of such FinTech firms could raise concerns regarding consumer protection and potentially threaten the stability of the overall financial system.

3.1.2 Digital lending

Since 2005, when the UK-based FinTech platform Zopa started offering digital lending services to its online customers, it has triggered the development of a new FinTech lending business model. Even though FinTech lending makes up only about 2% of the total credit market, it has been growing rapidly, with an impressive annual increase of 70% in recent years. As shown in Figure 3.1, FinTech credit lending increased from USD 11 billion to USD 284 billion between 2013 and 2016 (Claessens et al., 2018).

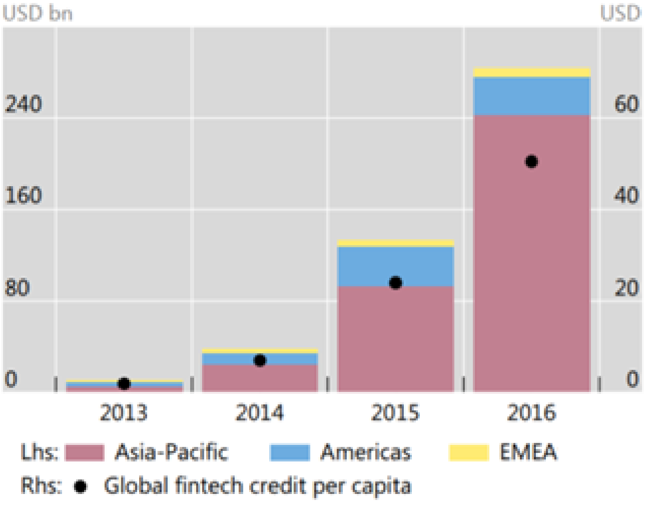

Figure 3.1: Worldwide FinTech credit volume (Claessens et al., 2018)

The chart displays a swift rise in the overall volume of FinTech credit from 2013 to 2016, with each region represented by a different color indicating its respective volume.

By providing an alternative approach for businesses and consumers to obtain financing, FinTech lending has expanded access to credit for previously underserved segments of the population. However, global FinTech transaction volumes experienced a decline after a period of rapid growth until 2017, mainly because China introduced stricter regulations (Elekdag et al., 2024).

In recent years, China and India have risen as centers for FinTech firms, alongside the United States and the European Union, which have been traditional leaders in digital banking services. Tencent and Alibaba stand as the leading FinTech firms in China, representing the Big Tech type group that offers digital lending services. In 2023, Tencent's WeChat Pay digital wallet had 1.1 billion active users. In addition, its WeBank offers micro-loans to consumers on the WeChat platform through its WeiLiDai product, allowing users to borrow up to 30,000 USD without formal collateral. Since 2010, Alibaba's Ant Group has been offering loans and short-term financing to vendors through its Alipay platform. With over 1.3 billion Alipay users, Ant Group's consumer lending arm serves around 500 million individuals through a "buy now, pay later" model, resulting in a cumulative borrowing of USD 270 billion primarily through partnerships with banks and trusts (McDonald, 2021). In certain instances, the lending was recorded on the balance sheets of Big Tech firms or their financial services subsidiaries, using funds sourced from wholesale markets (Cornelli et al., 2023).

In the United States, major Big Tech firms such as Apple, Google, and Facebook have all introduced digital credit products to provide their users with convenient financial services. Apple offers the Apple Card, integrated with the Apple Pay digital wallet. Google provides similar services through Google Pay, including Peer-to-Peer payments, mobile banking features, and merchant payment processing. Facebook offers digital credit via Facebook Pay across its platforms, such as Facebook, Instagram, Messenger, and WhatsApp.

FinTech firms operate as online-only lenders and digital wallet providers without physical branch offices, thus lowering barriers to entry into the banking services market. This new digital banking business model capitalizes on the internet and smartphones, generating considerable economies of scale when compared to capital-intensive traditional banks with thousands of physical branch offices.

3.2 Difference between FinTech and traditional banks

The past decade has witnessed exponential growth in the FinTech sector, driven by advancements in technology, changes in consumer behavior, and regulatory reforms.

FinTech involves the use of technology in various financial services, including payment processing and internet banking. FinTech lending refers to institutions without banking licenses ("non-bank") providing digital credit to consumers (Greenacre, 2020). In contrast, traditional commercial banks usually rely on in-person procedures at physical branches, whereas FinTech firms operate online without such branches, preferring digitalized customer interactions. The widespread use of mobile phones and associated payment services has helped the creation of FinTech lending models. These new FinTech digital lenders, offering mobile money and digital credit to the consumers of the younger generation through mobile phone-based payment services, have several advantages over traditional banks.

Firstly, FinTech is faster and easier. FinTech offers a quicker and more convenient alternative for financial transactions. Using the internet and smartphones, FinTech firms can reach underserved communities, particularly those lacking access to traditional banking services because of low income or geographical constraints. By allowing consumers to apply for loans remotely via smartphones, FinTech reduces transportation costs and eliminates the need for in-person visits to traditional banks. This accessibility enables FinTech firms to cater to low-income unbanked communities, providing them with mass consumer credit.

Secondly, FinTech is better for consumers. FinTech provides benefits for consumers by offering digital credit to individuals without a bank account or credit history. Utilizing machine learning algorithms, FinTech firms analyze collected data to assess consumers' financial risk profiles and make credit decisions rapidly. This enables them to offer customized small loans tailored to individual needs, albeit at higher interest rates. In countries such as the United States and the United Kingdom, FinTech credit constitutes a significant portion of unsecured personal loans and loans extended to small enterprises. In the United States, FinTech lending accounts for more than 30% of unsecured personal loans, while about 50% of total lending to small size enterprises in the United Kingdom (Claessens et al., 2018). Despite the absence of formal collateral requirements, FinTech firms operate on a high-risk, high-profit business model, using their credit pricing algorithms to determine default rates. As newcomers to the market, FinTech firms may choose to offer higher deposit rates as a strategic measure to secure funding and attract customers.

Thirdly, FinTech is cheaper to operate. FinTech offers a cost-effective operating model by eliminating the need for physical branch offices, thus significantly reducing overhead costs associated with traditional banks. Customers can conveniently apply for financial services remotely via mobile phones, eliminating the need for extensive physical infrastructure. This capital-light approach allows FinTech firms to operate with fewer fixed assets, resulting in lower operating costs and higher profit margins compared to traditional banks.

In summary, FinTech optimizes financial transactions with its innovative business model, making them faster, simpler, and cheaper. This creates opportunities for greater financial inclusion, extending access to services to individuals beyond the traditionally wealthy and privileged. As a result, consumers in both advanced and emerging economies are increasingly turning to digital financial services for their convenience, particularly among younger generations favoring digital banking over traditional banks with local branches.

Despite the ambitions of FinTech firms, particularly Big Tech companies, to expand into national or global financial markets, they often choose to operate outside traditional banking regulatory frameworks. This strategic choice is driven by the strict regulatory environment governing traditional banks, which includes capital requirements. As a result, Jackson (2020) found in his study that FinTech firms prefer to avoid the compliance burdens associated with direct regulation and supervisory oversight, leading them to remain outside the banking regulatory perimeters. However, as Rogoff (2017) noted in his book, it is one thing for a government to overlook the evolution of a promising new multipurpose technology, but quite another to allow its governance ability to be undermined.

3.3 FinTech Regulation

The heavily restricted banking regulations such as the Basel Accord could potentially hamper the operational efficiency and profitability of FinTech firms, making them more vulnerable to financial challenges. This poses a new regulatory dilemma for policymakers, given the distinctive business model of FinTech firms.

Initially, FinTech firms operated under the agent model as mentioned in the first category such as the P2P lending business, primarily offering financial services like transactions or investor matching without engaging in credit extension. However, there has been a shift towards more FinTech firms retaining loans on their balance sheets, resembling non-bank credit intermediaries. Consequently, claims from investors could lead to liquidity mismatches, raising the risk similar to a “FinTech platform run”.

In this paper, FinTech credit refers to credit provided by digital finance platforms, which differ from those managed by commercial banks. Despite FinTech firms benefiting from higher profits and lower operating costs, their novel business model blurs the definition of banks and raises concerns regarding consumer protection. Although FinTech firms provide consumer digital credit, a service traditionally associated with banks, they are not classified as commercial banks (Greenacre, 2020). As FinTech firms have the ability to reduce transaction costs and expand the range of services to unbanked communities, these efficiency-enhancing and access-expanding benefits offer possibilities to promote the public interest. However, the faster and tech-dominated new FinTech sector poses a fundamental regulatory challenge to the banking industry.

Unregulated FinTech firms can provide regulated financial services, yet traditional retail banking regulations struggle to define their activities unless new approaches are developed. Simply regulating the FinTech firms with the same regulation for traditional banks would generate huge compliance costs for those FinTech entrepreneurs’ activities and prematurely depress financial innovation, thus pushing them out of the market and causing considerable social harm.

The evaluation of FinTech default risks and failure factors has not been in-depth studied yet, partly because of the lack of bankruptcy cases of the newly created FinTech firms. Since those FinTech firms have not yet undergone a complete economic cycle, it remains uncertain how FinTech credit will perform under deteriorating business conditions. However, as newly established FinTech firms strive to expand, they may have a higher proportion of riskier borrowers, leading to increased default probabilities. Moreover, as rapidly growing FinTech firms gain market power and easily expand to new countries relying on internet access, there is a realistic threat that Big Tech firms such as Alibaba and Google could emerge as a new type of “too big to fail” financial institution.

The increasing regulatory scrutiny on FinTech credit platforms highlights a growing concern for consumer protection and financial stability. For instance, in Australia, FinTech firms are required to obtain a license to offer credit to consumers. In Germany, FinTech platforms are barred from lending without a banking license. In Spain, FinTech credit firms must meet minimum capital requirements. These regulations aim to mitigate the risks associated with FinTech lending, yet they inevitably introduce a balance between ensuring financial safety and encouraging innovation.

To protect consumer interests and ensure financial stability, there is an increasing need for empirical studies that predict the potential risks associated with innovative FinTech products and services. These studies are important for enhancing the effectiveness of regulatory decision-making processes. Therefore, this paper aims to examine the factors that contribute to the vulnerability of FinTech firms to financial distress during crises, analyzing the interaction between regulatory frameworks and market behaviors.

4 Data and Methodology

4.1 Data coverage

This paper conducts a cross-sectional analysis using accounting-based data from company balance sheets and income statements over a 6-year sample period from 2018 to 2023. Due to the unavailability of comprehensive financial data for all CAMELS variables of FinTech firms, a subset of 9 ratios is used as the nearest approximation. The data was obtained from the annual reports of 973 FinTech firms available in the S&P Capital One database, which serves as an extensive repository of accounting-based information for individual companies worldwide. This database uses standardized financial data from financial reports, thus ensuring comparability across countries and compliance with international accounting standards.

This paper investigates two global crises triggered by external factors during the study period: the COVID-19 pandemic in 2020-2021 and the Ukraine war in 2022-2023. First, binary choice regressions are applied to identify the factors influencing the financial distress of FinTech firms throughout the 2020-2021 pandemic period. Financial ratios extracted from annual reports of 2019 and 2018 are used as independent variables, representing one year and two years preceding the crisis, respectively. Afterward, the coefficients obtained from the COVID-based model are used to forecast the financial distress of FinTech firms in the 2022-2023 Ukraine war period, serving as an out-of-sample accuracy check for predictions.

The identification process of FinTech firms in financial distress relies on a customized function provided by the S&P database. The screener tool defined by the database allowed this analysis to filter out the distressed FinTech firms during the sample period (2020-2021) by defining specific event indicators, including “Seeking to Sell”, “Bankruptcy”, “Discontinued Operations”, “Auditor Going Concern Doubts”, “Credit Rating Downgrade”, and “Debt Defaults”. This standard filter effectively reduces the selection bias of the data collection.

The robustness check section applies ordinal regression with ordered response models (ORM) to expand the concept of financial distress. A FinTech firm is categorized as a *Fail* if its equity value drops below zero during the study period, as reported in the S&P database. Therefore, the baseline dataset of FinTech firms encountering financial difficulties during 2020-2021 is divided into three distinct levels: *Fail*, *Distress*, and *Normal*.

4.2 Explanatory variables

In this paper, CAMELS-type variables are calculated and applied as explanatory variables for regression analysis. Each of these variables reflects different aspects of a FinTech firm's financial health and performance. However, due to data availability constraints, there is always a trade-off between the number of explanatory variables and the sample size, as not all banks disclose the necessary financial information required to calculate every CAMELS ratio. Betz et al. (2014) stated that adding extra variables not only decreases the number of banks available for observations but also fails to enhance the performance of the model. Kočenda and Vojtek (2011) argued that including a large number of variables could introduce an increased number of degrees of freedom, which may lead to overfitting issues. Therefore, this paper selects 9 financial ratios that at least cover all types of CAMELS groups. ***C****apital adequacy* is represented by *Debt Ratio* (DR) and *Leverage Ratio* (LR), ***A****sset quality* by *Gross Margin* (GM) and *Profit Margin* (PM), ***M****anagement quality* by *Asset Turnover* (AsTo), ***E****arnings* by *Return on Assets* (RoA) and *Return on Equity* (RoE), ***L****iquidity* by *Current Ratio* (CR), and ***S****ensitivity to market risk* by *Revenue Growth* (RvG). Table 4.1 summarizes the definitions of explanatory variables, along with their corresponding CAMELS group.

Table 4.1: Definitions of CAMELS-type variables

CAMELS	Variable	Formula	Definition
Capital adequacy	Debt Ratio (DR)	$\frac{Total\ Liabilities}{Total\ Assets}$	Indicates the percentage of a company's assets financed through debt.
	Leverage Ratio (LR)	$\frac{Total\ Debt}{Total\ Equity}$	Determines a company's debt relative to its equity.
Liquidity	Current Ratio (CR)	$\frac{Current\ Assets}{Current\ Liabilities}$	Measures a company's ability to meet short-term obligations that are due within a year.
Management quality	Asset Turnover (AsTo)	$\frac{Revenue}{Total\ Assets}$	Evaluates how efficiently a company converts its assets into sales revenue.
Sensitivity to market risk	Revenue Growth (RvG)	$\frac{Revenue_t - Revenue_{t-1}}{Revenue_t}$	Refers to the percentage increase in sales over a one-year period.
Earnings	Return on Assets (RoA)	$\frac{Net\ Income}{Total\ Assets}$	Indicates a company's profitability relative to its total assets.
	Return on Equity (RoE)	$\frac{Net\ Income}{Total\ Equity}$	Measures the efficiency with which a company generates income from the equity investments of its shareholders.
Asset quality	Gross Margin (GM)	$\frac{Revenue - Cost}{Revenue}$	Refers to the portion of a company's revenue remaining after subtracting direct costs.
	Profit Margin (PM)	$\frac{Net\ Income}{Revenue}$	Measures the profit a company generates from its products or services after deducting all direct and indirect costs.

This paper introduces a new evaluation approach called the CFS framework, inspired by the Cash Flow Statement, which organizes company accounting elements into financing, operating, and investing categories. Within the CFS framework, the paper classifies the CAMELS-type ratios into three subgroups according to their economic impact on the performance of FinTech firms. Specifically, *Capital Adequacy* reflects the performance within the financing category, *Operating Activities* indicates the competitive capability of the firm within the operating category, and *Profitability* represents shareholder returns within the investing category.

The effects of most financial ratios on the probability of FinTech firms experiencing financial distress can be predicted based on economic theory. For example, a higher debt ratio is expected to increase the distress likelihood. Table 4.2 provides descriptions of each selected variable and its expected impact on financial distress. The 9 selected proxy ratios of CAMELS factors are grouped into a new CFS framework comprising three categories: *Capital Adequacy*, *Operating activities*, and *Profitability*.

Table 4.2: Independent variables in the CFS Framework

CFS Category	Variable	Expected Impact
Capital Adequacy	Debt Ratio (DR)	(+) Level of solvency
	Leverage Ratio (LR)	(+) Level of leverage
	Current Ratio (CR)	(-) Level of liquidity
Operating Activities	Asset Turnover (AsTo)	(-) Operational efficiency
	Revenue Growth (RvG)	(-) Source of economic benefit
Profitability	Return on Assets (RoA)	(-) Capacity of generating values
	Return on Equity (RoE)	(-) Ability to generate profit
	Gross Margin (GM)	(-) Competitive position
	Profit Margin (PM)	(-) Competitive ability

In this paper, market-based variables are excluded from consideration for two reasons. Firstly, the analysis focuses on a longer time horizon ranging from one to two years. As mentioned by Betz et al. (2014), market-based indicators are effective for only a short period preceding bank distress. Secondly, this paper covers both listed and private FinTech firms in the sample, further justifying the exclusion of market-based variables.

Besides the financial variables at the firm level discussed earlier, this paper incorporates the *Size* factor along with other non-financial variables. The definitions of the non-financial variables are presented in Table 4.3.

Table 4.3: Definitions and expected impacts of non-financial variables

Variable	Definition	Expected Impact
Size (log value)	The natural logarithm of the Total Assets value of the FinTech Firm.	(-) The larger the size, the less likely to experience distress, making it too big to fail.
Age (dummy)	1 if the FinTech firm is more than 10 years old, 0 otherwise.	(-) The greater the management's experience, the lower the risk of financial distress.
Public (dummy)	1 if the FinTech firm is a public listed company, 0 otherwise.	(-) The easier access to funding from capital markets, the less likely to experience distress.
Location (dummy)	1 if the FinTech firm is in a developed country, 0 otherwise.	(-) The more favorable business environment, the lower likelihood of distress.

When selecting explanatory variables, it is important to consider the issues of endogeneity and multicollinearity. Endogeneity refers to the situation where the explanatory variables are correlated with the error term in the regression model, leading to biased coefficient estimates. Kočenda and Iwasaki (2020) suggested that if all independent variables are considered predetermined, the endogeneity issue between dependent and independent variables could be minimized. Likewise, Berger and Bouwman (2013) used sample data of independent variables prior to a crisis to analyze their impact on bank performance, arguing that this approach can mitigate endogeneity concerns by reducing the likelihood of joint determination between lagged explanatory variables and current bank performance.

In this paper, the explanatory variables are derived from the firm-level annual financial reports of 2018 and 2019, while the dependent variable is represented by a discrete dummy value indicating whether the FinTech firm encountered distress during the period of 2020-2021. By selecting explanatory variables from earlier periods, this paper reduces the likelihood of causal relationship between the explanatory variables and the occurrence of distress. This approach enhances the robustness of the analysis and strengthens the validity of the findings by minimizing the risk of endogeneity bias.

Multicollinearity occurs when two or more explanatory variables are highly correlated with each other, making it difficult to estimate their individual effects accurately. Therefore, this paper utilizes strategies such as eliminating redundant variables or selecting only one variable from each highly correlated pair, using a correlations matrix, to address the multicollinearity issue.

4.3 Descriptive statistics

This part includes several sections: Summary statistics for explanatory variables, correlations matrix for variable selection, statistics for out-of-sample testing dataset, and statistics for ordered distressing levels data.

4.3.1 Summary statistics for explanatory variables

This paper calculates CAMELS-type ratios for each FinTech firm based on annual report financial data. However, the presence of outliers in the independent variables raises significant concerns regarding potential bias in the results. Therefore, this paper follows a methodology similar to that of previous studies to mitigate the issue of extreme outliers. Specifically, the data preparation is conducted using the Winsorize function developed by Signorell et al. (2021) to address extreme 0.1 percent outliers in the calculated ratios. The summary statistics of post-winsorization results presented below provide a comprehensive overview of the dataset.

Table 4.4: Descriptive statistics on variables – Baseline dataset

Variable	Distress (83)				Normal (830)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
FD	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00
DR	59.46	24.27	9.14	98.99	53.70	24.55	0.40	99.87
LR	4.86	12.70	0.10	93.63	5.14	34.80	0.00	718.55
CR	2.51	4.11	0.05	31.61	7.20	81.88	0.05	2222.41
AsTo	62.16	50.16	0.58	282.61	114.27	193.94	0.49	2922.68
RvG	19.11	100.05	-89.66	634.15	77.41	1338.56	-99.59	28276.23
RoA	-10.09	33.70	-164.59	22.99	2.84	23.36	-334.54	126.08
RoE	-227.08	1341.25	-9508.20	44.94	-19.79	423.50	-9797.49	647.06
GM	49.82	36.05	-141.83	100.00	60.42	34.33	-140.54	102.17
PM	-61.05	237.53	-1479.89	38.74	4.20	99.09	-1412.21	1497.07
Size	5.68	3.07	-0.56	12.10	4.19	2.20	-1.56	12.32
Age	0.83	0.38	0.00	1.00	0.87	0.34	0.00	1.00
Pub	0.75	0.44	0.00	1.00	0.39	0.49	0.00	1.00
Loc	0.58	0.50	0.00	1.00	0.60	0.49	0.00	1.00

Note: All variables have been winsorized at 0.1 percent of each tail.

Table 4.4 presents the descriptive statistics of both the explanatory variables and the response variable, *Financial Distress* (FD). The results are based on data extracted from the 2019 annual reports of 973 FinTech firms. Among these firms, 83 were identified as being financial distressed, meaning that they met at least one of the following criteria during the 2-year period of 2020-2021: “Seeking to Sell”, “Bankruptcy”, “Discontinued Operations”, “Auditor Going Concern Doubts”, “Credit Rating Downgrade”, and “Debt Defaults”.

4.3.2 Correlations matrix for variable selection

This paper applies explanatory CAMELS-type variables as proxies in logit and probit regression models to analyze the effects of FinTech fundamentals. Lin and Yang (2016) argued that even when it is possible to obtain all 29 CAMELS ratios, a Pearson’s correlation analysis should be applied to handle the potential redundancy and multicollinearity problems that may occur with a large set of financial variables. Kočenda and Iwasaki (2020) applied a correlation matrix to examine the CAMELS variables used in their empirical analysis. They determined that correlations between variables below 0.55 did not result in an issue of multicollinearity.

Following the outlined guiding principles, this paper employs correlation analysis to manually select potential explanatory variables. The Bayesian model averaging (BMA) approach is also applied for variable selection in the robustness check section later in this paper.

Table 4.5: Correlations between CAMELS variables

	DR	LR	CR	AsTo	RvG	RoA	RoE	GM	PM
DR	1.000								
LR	0.219	1.000							
CR	-0.124	-0.011	1.000						
AsTo	0.043	0.002	-0.027	1.000					
RvG	0.014	0.018	-0.004	0.299	1.000				
RoA	-0.101	-0.056	0.008	0.079	0.029	1.000			
RoE	-0.135	-0.493	0.006	0.029	-0.003	**0.429**	1.000		
GM	0.075	0.007	0.038	-0.161	-0.010	0.140	0.034	1.000	
PM	-0.060	-0.027	0.183	0.016	-0.009	**0.618**	0.274	0.142	1.000

Table 4.5 reports the results of the correlation analysis employed to identify financial variables with lower correlations. The correlations between the same type of CAMELS indicators are generally high. For example, the correlation between *Return on Assets* (RoA) and *Return on Equity* (RoE) is 0.429, and the correlation between *Profit Margin* (PM) and *Return on Assets* (RoA) is 0.618. Therefore, for these highly

correlated pairs, a selection is conducted so that only one variable from each pair is kept for further analysis.

Table 4.6: Correlations matrix of selected variables

	DR	CR	AsTo	RvG	RoA	GM
DR	1.000					
CR	-0.124	1.000				
AsTo	0.043	-0.027	1.000			
RvG	0.014	-0.004	0.299	1.000		
RoA	-0.101	0.008	0.079	0.029	1.000	
GM	0.075	0.038	-0.161	-0.010	0.140	1.000

Table 4.6 displays the correlation matrix results after removing one variable from each highly correlated pair of the same type of CAMELS variables so that all of the 6 CAMELS-type classes are still represented. Namely, ***C**apital adequacy* is represented by *Debt Ratio* (DR), ***A**sset quality* by *Gross Margin* (GM), ***M**anagement quality* by *Asset Turnover* (AsTo), ***E**arnings* by *Return on Assets* (RoA), ***L**iquidity* by *Current Ratio* (CR), and ***S**ensitivity to market risk* by *Revenue Growth* (RvG). The absolute values of correlation coefficients of all the remaining explanatory variables are below 0.3. In this way, the low pairwise correlation levels effectively mitigate the issue of multicollinearity.

4.3.3 Out-of-sample data statistics

In this paper, the dataset of FinTech firms experiencing distress triggered by the COVID-19 crisis serves as training data. Baseline logistic regression models are used to identify the factors influencing the financial distress of FinTech firms during the pandemic period of 2020-2021. The coefficients obtained from the COVID-based model are subsequently applied to predict the financial distress during the Ukraine war period of 2022-2023, which serves as an out-of-sample testing dataset.

The CAMELS ratios of FinTech firms in the testing dataset are examined using financial data from the 2021 annual reports. Subsequently, the same filter in the S&P database is applied to select the distressed FinTech firms during the period of 2022-2023. Table 4.7 reports the descriptive statistics of the variables from 2021, where the firms are divided based on their status into *Distress* and *Normal* samples.

Table 4.7: Descriptive statistics on variables – Testing dataset

Var	Distress (96)				Normal (843)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
FD	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00
DR	49.98	24.56	1.34	91.57	53.44	24.46	-2.94	99.56
LR	1.88	2.25	0.01	10.86	4.08	16.65	-0.02	351.97
CR	4.27	6.93	0.06	32.71	3.76	12.01	0.06	231.69
AsTo	58.47	80.80	1.01	681.65	101.51	158.62	0.33	3091.65
RvG	32.72	73.99	-95.91	371.43	54.30	555.82	-96.16	10962.72
RoA	-12.58	37.26	-240.58	52.60	3.87	29.29	-279.73	304.33
RoE	-27.24	79.96	-404.67	52.60	29.71	1345.35	-6523.88	37661.15
GM	50.36	39.04	-167.17	100.83	55.80	36.82	-175.34	163.00
PM	-56.68	299.97	-1733.88	1647.25	25.12	446.00	-1634.41	8008.58

For each FinTech firm, its CAMELS-type ratios are calculated from the 2021 annual report financial data. After winsorizing the extreme 0.1 percent outliers, the analysis captures the sample size of 939 FinTech companies, of which 96 were in financial distress during the 2-year period of 2022-2023, meaning that they met at least one of the following criteria: “Seeking to Sell”, “Bankruptcy”, “Discontinued Operations”, “Auditor Going Concern Doubts”, “Credit Rating Downgrade”, and “Debt Defaults”.

4.3.4 Ordered distressing levels

To create the sample for the ordered logit regression conducted in the robustness check section, the baseline training dataset is further segmented. Specifically, the FinTech firms are divided into three levels of *Fail*, *Distress*, and *Normal* to make the dependent variable *Order* ordinal. Table 4.8 shows the descriptive statistics of financial ratios for FinTech firms under different financial distress levels.

Table 4.8: Descriptive statistics for ordered distress levels

Var	Fail (12)				Distress (71)				Normal (890)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Order	2.0	0.0	2.0	2.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0
DR	70.6	24.2	15.8	98.6	57.6	24.0	9.1	99.0	53.7	24.6	0.4	99.9
CR	0.8	0.3	0.4	1.4	2.8	4.4	0.1	31.6	7.2	81.9	0.1	2222.4
AsTo	45.4	39.8	3.5	147.7	65.0	51.4	0.6	282.6	114.3	193.9	0.5	2922.7
RvG	34.1	140.1	-68.5	457.4	16.6	92.7	-89.7	634.2	77.4	1338.6	-99.6	28273.2
RoA	-53.2	62.2	-164.6	2.0	-2.8	18.7	-84.6	23.0	2.8	23.4	-334.5	126.1
GM	37.7	67.0	-141.8	97.7	51.9	28.1	9.5	100.0	60.4	34.3	-140.5	102.2

The summary statistics of variables are calculated based on data from the 2019 annual reports of 973 FinTech firms. Among these firms, 890 are labeled as *Normal*, and their statistical results are consistent with those in baseline analysis. The remaining 83 firms are further divided into two levels, with *Fail* representing 12 FinTech firms with more severe financial difficulties, as their equity value was lower than zero during the two-year period of 2020-2021, and *Distress* including 71 FinTech firms that met at least one of the following conditions: “Seeking to Sell”, “Bankruptcy”, “Discontinued Operations”, “Auditor Going Concern Doubts”, “Credit Rating Downgrade”, and “Debt Defaults”. The findings indicate that FinTech firms facing worse financial distress tend to exhibit a higher *Debt Ratio* (DR) but lower *Return on Assets* (RoA) and *Gross Margin* (GM).

4.4 Data rebalancing

Due to the nature of bankruptcy, it is typical for data samples to contain a significantly lower number of FinTech firms experiencing financial distress compared to those operating normally, resulting in a high level of imbalance in the dataset. Therefore, this paper tries to create rebalanced datasets and examine them against the original training data to validate the robustness of the baseline model results.

Common methods for addressing rare events involve adjusting the class distribution of the original dataset to achieve a more balanced sample, such as by increasing the representation of the minority class through over-sampling, reducing the prevalence of the majority class via under-sampling, or using a combination of both techniques, sometimes complemented by a bootstrap method and synthetic data generation. Lunardon et al. (2014) implemented these methods of rebalancing the datasets in their Random Over-Sampling Examples (ROSE) package. Figure 4.1 provides a visual representation of these methods with their corresponding results.

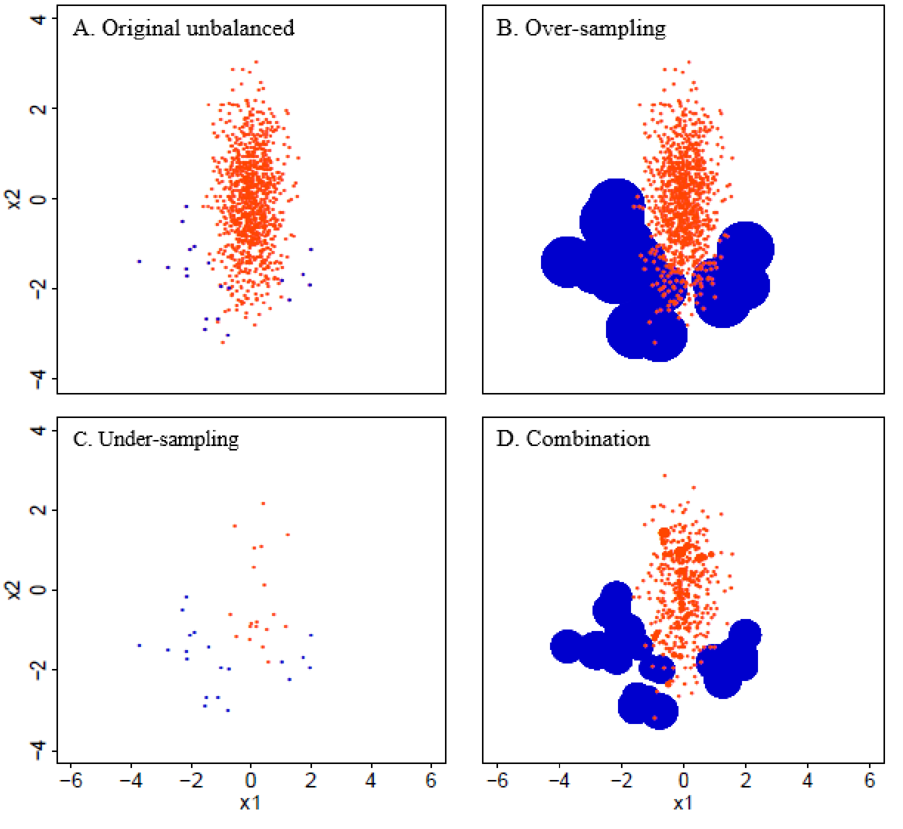

Figure 4.1: Data rebalancing approaches and results (Lunardon et al., 2014)

The majority and minority class examples are represented by orange and blue colors, respectively. Chart A exhibits the original unbalanced training data; Chart B illustrates the result of the over-sampling approach; Chart C displays the outcome of the under-sampling approach; and Chart D shows the result of a combination of over- and under-sampling with the same sample size as the original data.

In the illustration provided by Lunardon et al. (2014) as Figure 4.1, Chart A displays a visual representation of the original unbalanced training dataset. Chart B demonstrates the implementation of the over-sampling method, which involves artificially increasing the number of instances in the minority class by replicating them. In contrast, Chart C illustrates the under-sampling approach, where instances from the majority class are randomly reduced to match the size of the minority class. Finally, Chart D exhibits the outcome of a combined method, using both over- and under-sampling techniques to balance the dataset, ensuring it maintains the same size as the original training data.

4.5 Empirical models

This part encompasses several sections: Binary Choice Models (BCM), Ordered Response Models (ORM), and Bayesian Model Average (BMA).

4.5.1 Binary choice models

This paper uses empirical models to evaluate the determinants of FinTech firms in distress that occurred during the COVID-19 period. The dependent variable *Financial Distress* is binary, taking the value of 1 if a FinTech firm is in financial distress and 0 otherwise. Due to the nature of dependent variables, this paper applies the binary response models where the dependent variable is an indicator reflecting a binary classification.

Both probit and logit models are used due to their established presence in the literature and their effectiveness in addressing tasks related to failure prediction. This paper assumes that dependent variable y represents an unobservable index indicating the probability of a FinTech firm experiencing financial distress over the 2-year period from 2020 to 2021. This probability is considered as a function of firm-level specific characteristics x, expressed by the equation:

$$P(y=1|x)=F(\beta_0+\beta_1 x_1+\ldots+\beta_n x_n+\mu)\,, \tag{4.1}$$

where x represents a set of financial ratios of FinTech firms extracted from the annual reports of the financial year ending in 2019. The vector β represents the parameter estimates for the explanatory variables, reflecting the relationship between the identified financial ratios and the unobservable probability index of distress. This formulation serves as the foundation for evaluating the potential impact of the selected financial indicators on the likelihood of financial distress within the FinTech sector during the specified 2-year period.

The logit model specifies $F(\cdot)$ as a cumulative distribution function (CDF) with a logistic distribution, where $F(x)=\Lambda(x)$:

$$P(y=1|x)=\frac{e^{x'\beta}}{1+e^{x'\beta}}=\Lambda(x'\beta)\,, \tag{4.2}$$

while the probit model applies CDF with a standard normal distribution $\phi(x)$, with $F(x)=\Phi(x)$:

$$P(y=1|x)=\int_{-\infty}^{x'\beta}\Phi(t)\,dt=\Phi(x'\beta). \tag{4.3}$$

The key difference between the two models lies in the cumulative distribution function selected to determine the likelihood function. Figure 4.2 shows the distribution functions of logistic and normal distribution.

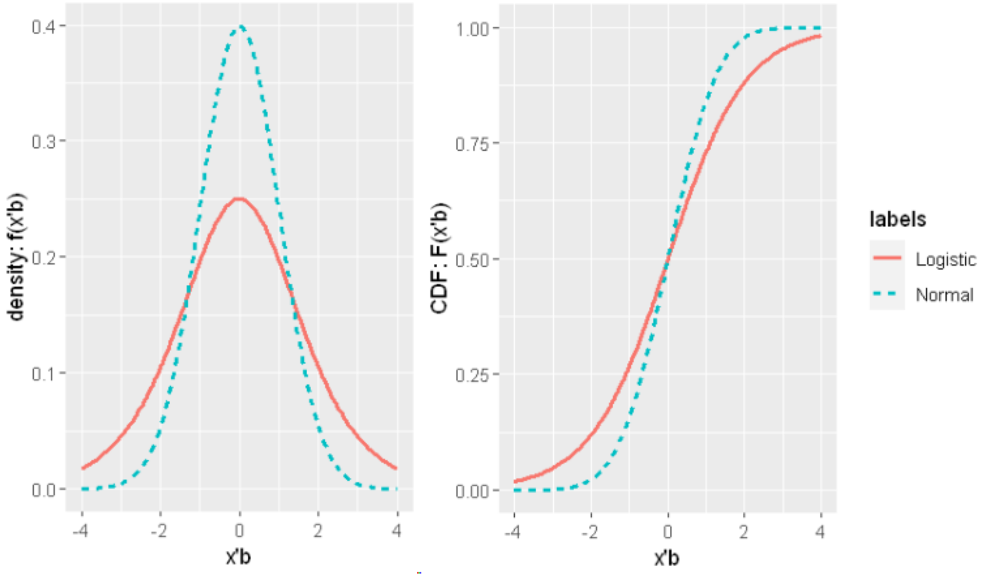

Figure 4.2: Logistic and Normal functions

The red solid line is a logistic function, while the blue dash line is a standard normal function. The left side shows the density of two functions; the right side shows the cumulative distribution functions.

Both logit and probit models are nonlinear, with the logit model exhibiting slightly flatter tails compared to those of a normal distribution. Overall, the characteristics of probit and logit models are quite similar. Gelman and Hill (2006) suggested that dividing the coefficient estimates from a logit model by 1.6 can approximate the coefficients of a probit model. Stock and Watson (2006) also stated that probit and logit regressions give very similar results, but the logistic approach is traditionally favored for its ease of implementation. In their study spanning from 1985 to 2004 across 13 countries, Van den Berg et al. (2008) noted that, compared to probit regression, the logit model is more suitable for predicting rare events such as financial crises. Considering the findings of the above research, this paper uses logit regression as the baseline model, while the probit model is applied for comparison purposes.

The marginal effect represents the change in the predicted value of the dependent variable associated with a change in the independent variable. In the ordinary least squares (OLS) model, the marginal effects are straightforwardly represented by the estimated coefficients. However, in the logit model, due to the nonlinear nature of predicted probabilities and estimated partial effects, the coefficients alone cannot directly reflect the marginal effects and require further interpretation. To establish the relationship between changes in the predicted dependent variable and the independent variable in the logit model, the marginal effect is used:

$$\frac{\partial F(z_i)}{\partial x_{j,i}} = \widehat{\beta}_j f\left(\widehat{\beta}' x_i\right), \tag{4.4}$$

where $\frac{\partial F(z_i)}{\partial x_{j,i}}$ represents the partial derivative of the predicted probability concerning the independent variable $x_{j,i}$, where z_i denotes the predictor for the i-th observation in the dataset, while $\widehat{\beta}_j$ is the estimated coefficient associated with the independent variable $x_{j,i}$, and $f\left(\widehat{\beta}' x_i\right)$ represents the derivative of the logistic function concerning the linear predictor $\widehat{\beta}' x_i$. This formula shows how changes in the independent variable influence the predicted probabilities within the logit model.

The marginal effect of nonlinear functions can be measured through either the sample average or by calculating the average of all partial effects. This paper uses the former approach, known as the sample-mean method. This method involves selecting a “typical” value of x, which is at the mean, and subsequently evaluating the effect of this typical value.

In linear regression, the R-squared statistic is commonly used to evaluate the goodness of fit. However, when applied to logit and probit models, this metric can be misleading due to the binary nature of the observed values. The disparity arises from a fundamental difference in these models, where the predicted values can span a continuous range of possibilities, but the actual observed values in logit and probit models are binary limited to only values of one or zero. Therefore, this paper applies the Pseudo-R-squared by McFadden (1973), also known as the Likelihood Ratio Index (LRI), to measure the goodness of fit for logit and probit models. The LRI formula, expressed as:

$$LRI = 1 - \frac{L_1}{L_0}, \tag{4.5}$$

where L_1 is the likelihood of a simpler model with fewer parameters, while L_0 is the likelihood of the full model which includes additional parameters.

The LRI measures the improvement in model fit when moving from the L_1 simpler model to the L_0 full model, with values ranging between 0 and 1. Higher values indicate a better fit. However, unlike R-squared, the absolute value of LRI does not offer a direct interpretation. The significance of LRI lies in its ability to compare models of the same type. For example, comparing probit and logit models based on LRI yields meaningless results as their likelihood functions differ.

4.5.2 Ordered response models

As FinTech firms experiencing financial distress can be categorized into several groups with increasingly severe problems, the ranking of subgroups provides additional information regarding different levels of distress severity. Given that the dependent variable assumes multiple values and demonstrates an ordinal nature, the ordered logit model appears to be well-suited for the situation (Kick and Koetter, 2007). This paper applies both the ordered logit model and the ordered probit model to the dataset, in which observations are categorized into three ordered groups to verify the robustness of the results obtained from the original data model.

One common type of ordered response model is the ordered logit regression. Within this model, it is assumed that the natural logarithm of the odds of an observation belonging to a category at or below a certain threshold versus above it, exhibits a linear relationship with the independent variables. The model is formulated as follows:

$$logit\left(p\left(Y \leq j \middle| X\right)\right) = \alpha_j - \beta X\,, \tag{4.6}$$

where $p(Y \leq j)$ represents the probability of the dependent variable Y falling at or below a threshold j, given the values of the independent variables X. Meanwhile, α_j represents the intercept specific to the j-th threshold, and β is a vector of coefficients for the independent variables X.

Ordered response models are used to deal with the ordinal nature of categorical dependent variables. This paper assumes that when a FinTech firm experiences financial difficulties, based on the intensity of the problems, the distressing level can be scaled from *Normal* up to *Distress*, with *Fail* being the final potential outcome. The dependent variable *Order* takes on distinct values as follows:

- 0: Indicates a non-distressed state of the FinTech firm (*Normal*),
- 1: Means distress based on the index filter (*Distress*),
- 2: Indicates a state where the firm's equity is less than zero, as indicated in the S&P database. (*Fail*).

4.5.3 Bayesian model average

Lin and Yang (2016) identified 29 financial ratios within the CAMELS framework for their study on bank failures from 1999 to 2011, but they selected only 9 based on low correlations. In his analysis of banking crises from 1980 to 2010 with 13 benchmark variables, Hamdaoui (2016) highlighted the challenge of uncertainty in selecting the correct set of variables for regression. Including all potential variables into a single regression would lead to inflated standard errors due to the possible inclusion of irrelevant variables. To address this issue, he proposed the use of the Bayesian model averaging (BMA) approach, which evaluates model combinations and assigns weights based on their goodness of fit.

The BMA method applies Bayesian inference to systematically reduce uncertainty in model selection. It applies regressions on various subsets of potential variable combinations, with the likelihood of each model determined by the Posterior Model Probability (PMP). The decision on which variables to include in the model is guided by the Posterior Inclusion Probability (PIP) calculated across various models (Kočenda and Iwasaki, 2022).

Let $M = (M_1, \dots, M_{2^k})$ represent the set of models being considered, where k candidate regressors varying based on the regression specification. Each model M_j is characterized by the subset of variables it includes, resulting in 2^k combinations and uncertainty regarding the optimal model selection. If β represents the quantity of interest, such as a model parameter, then the posterior distribution of β given data Z is expressed as:

$$p(\beta|Z) = \sum_{j=1}^{2^k} p(\beta|Z, M_j)\, p(M_j|Z), \tag{4.7}$$

under the assumption that M_j is the "true" model. This represents an average of the posterior predictive distribution under each of the models considered, weighted by the corresponding PMP as $p(M_j|Z)$. The robustness of a variable of interest is evaluated by examining its associated PIP formulated as follows:

$$PIP_i = \sum_{M: m_i = 1}^{2^k} p(M_j|Z), \tag{4.8}$$

where $m_i = 1$ indicates the inclusion of variable i in the model. Therefore, the PIP of a particular variable is the sum of the PMPs of all models that include this variable, which can serve as a measure of the significance of a variable in explaining the observation under analysis. To handle a large number of models, researchers commonly use the Markov Chain Monte Carlo (MCMC) approach to explore the model space. However, since this paper deals with only 9 CAMELS variables due to constraints in data availability, fully enumerating the model space is feasible, resulting in a total of $2^9 = 512$ models.

It is important to recognize that while model averaging addresses uncertainties in model selection, it does not resolve underlying issues such as multicollinearity and correlations within the dataset. Therefore, it is essential to remain mindful of correlations when interpreting the results (Feldkircher, 2014). To address this concern, this paper performs a correlation check after the BMA analysis to identify the appropriate variables for selection.

4.6 Prediction evaluation

The Receiver Operating Characteristics (ROC) methodology is widely used in failure prediction studies, as it helps in visualizing the trade-off between hit rates and false alarm rates of classifiers (Fawcett, 2006). This method is particularly valuable for evaluating the performance of classification models and adjusting thresholds to manage Type I (missing signal) and Type II (false alarm) errors. In their study of predicting bank distress in Europe, Betz et al. (2014) applied the ROC curves to demonstrate the model's sensitivity to variation in thresholds. This paper uses a similar approach to examine the out-of-sample forecast performance of the logit model.

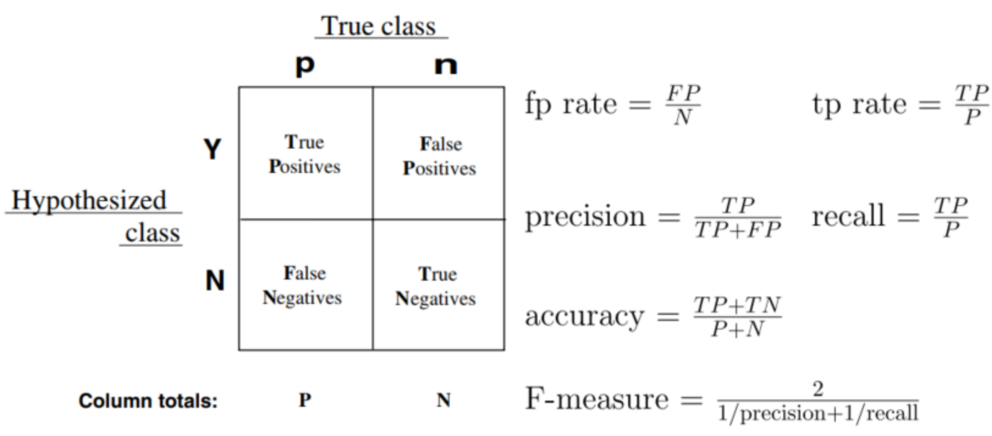

Figure 4.3: Confusion matrix (Fawcett, 2006)

The actual values of samples correspond to the set {p, n}, whereas predicted classes are labelled {Y, N}. On the right side are the related formula definitions.

A classifier is a tool that decides which class a sample belongs to by applying different thresholds. In a confusion matrix or contingency matrix, as shown in Figure 4.3, each sample is labeled as either positive (p) or negative (n) based on its actual class, while the predicted class is either Y (yes) or N (no). The true positive rate (TPR), also known as the "hit rate", is calculated using the following formula:

$$TPR = \frac{TP}{P} = \frac{Positive\ correctly\ classified}{Total\ positives} = Sensitivity\ . \qquad (4.9)$$

The true negative rate (TNR), serving as an indicator of "specificity", is determined by the following formula:

$$TNR = \frac{Negatives\ correctly\ classified}{Total\ negatives} = Specificity\ . \qquad (4.10)$$

The false positive rate (FPR), representing the "false alarm rate", is calculated as follows:

$$FPR = \frac{FP}{N} = \frac{Negatives\ incorrectly\ classfied}{Total\ negatives} = 1 - Specificity\ . \qquad (4.11)$$

In the ROC graph, the vertical axis represents the true positive rate, whereas the horizontal axis indicates the false positive rate. Each classifier generates a pair of true positives (benefit) and false positives (cost), which corresponds to a single point in the ROC space. Kočenda and Vojtek (2011) explained that navigating along the ROC curve involves balancing false positive cases against false negative cases. Figure 4.4 displays several typical examples of the ROC curves.

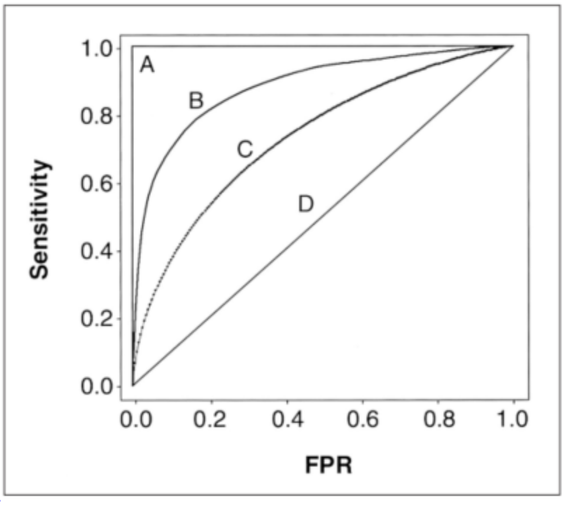

Figure 4.4: Four ROC curves with different AUC (Park, 2004)

Curve A is a perfect test with the Area Under the ROC Curve (AUC) of 1; Curve D is a chance diagonal with the AUC of 0.5; Curve B with the higher AUC has a better overall performance than Curve C.

The ROC curve generally shows an upward slope, passing through the points (0,0) and (1,1). Lowering the threshold means saying "yes" to more samples, which results in catching more positive ones but also misclassifying some negative ones. On the contrary, raising the threshold means saying "yes" less often, which leads to catching fewer positive samples but also making fewer mistakes by misclassifying negative ones.

In the example of Figure 4.4, Curve A, marked by the point (0,1), represents perfect classification, where all positive samples are accurately classified without any false positives. Conversely, the diagonal line of Curve D spanning from (0,0) to (1,1), symbolizes random guessing, where approximately half of the positive and negative instances are correctly identified. Generally, a point closer to the top-left quadrant on the ROC graph signifies superior performance, reflecting a higher true positive rate (TPR, or Sensitivity) coupled with a lower false positive rate (FPR).

Hanley and McNeil (1982) proposed calculating the Area Under the ROC Curve (AUC) as a common method for comparing classifiers. In the ROC graph of example Figure 4.4, random guessing represented by Curve D has an AUC area of 0.5, whereas Curve A which represents perfect classification, has an AUC of the maximum value 1. Compared to Curve C, Curve B has a better average performance as its AUC is larger, implying a better ability to discriminate between positive and negative samples. Any classifier that is better than random selection should have an AUC greater than 0.5.

5 Results and Discussion

5.1 Empirical regression results

Table 5.1 presents the outcomes of a series of logit and probit regressions, constituting the main findings of this paper.

Table 5.1: Regression results of 2019 and 2018

Variable	Logit 2019	Probit 2019	Logit 2018	Probit 2018
Debt Ratio	0.009*	0.005*	0.006	0.003
	(0.005)	(0.003)	(0.005)	(0.002)
Credit Ratio	-0.019	-0.009	-0.006	-0.003
	(0.024)	(0.011)	(0.013)	(0.006)
Asset Turnover	-0.008***	-0.004***	-0.007***	-0.003***
	(0.002)	(0.001)	(0.002)	(0.001)
Revenue Growth	-0.0002	-0.0001	-0.0003	-0.0001
	(0.001)	(0.0004)	(0.001)	(0.0003)
Return on Assets	-0.009**	-0.005**	-0.019***	-0.011***
	(0.004)	(0.002)	(0.004)	(0.003)
Gross Margin	-0.009***	-0.005***	-0.004	-0.002*
	(0.003)	(0.002)	(0.002)	(0.001)
Constant	-1.644***	-0.959***	-1.910***	-1.085***
	(0.406)	(0.206)	(0.368)	(0.187)
Observations	973	973	979	979
Log Likelihood	-261.110	-259.668	-267.199	-266.552
AIC	536.219	533.335	548.399	547.104

Note: The dependent variable is Financial Distress (FD). The symbols ***, **, and * represent statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

The dependent variable in these models takes a value of one if a FinTech firm experienced financial distress during the 2020-2021 period, and zero otherwise. The first two columns display outcomes obtained from annual report data collected in 2019, one year before the COVID-19 pandemic, while the last two columns show the coefficient results based on financial ratios from 2018, two years prior to the crisis.

The results obtained are mostly in line with expectations. In all cases, the signs of the estimated coefficients in the regression are generally consistent with expectations. However, it is noteworthy that *Revenue Growth* (RvG) and *Current Ratio* (CR) do not exhibit statistical significance in the analysis. Across both years preceding the crisis, the signs of the coefficients of all ratios remain consistent. The variables from the year 2019 exhibit lower Akaike Information Criterion (AIC) values compared to those from 2018, indicating that the more recent financial ratios have greater influence in the analysis. Variables that are statistically significant in 2019 also show significance in the preceding year of 2018, although at reduced levels. This trend suggests a certain level of consistency in the impact of variables on the likelihood of financial distress across both years, but the strength of this impact diminishes in the earlier year, which is further from the crisis.

For *Capital Adequacy*, the results show that both *Debt Ratio* (DR) and *Current Ratio* (CR) exhibit the expected signs. These ratios directly reflect the level of indebtedness, a key concern for financially distressed companies during crises. Interestingly, the analysis results from both logit and probit models suggest that while *Debt Ratio* representing the long-term liability is significant, *Current Ratio* reflecting the short-term liquidity is not. *Debt Ratio* thus appears to have a more substantial impact in explaining FinTech distress likelihood. However, since its coefficient is significant only at the 10% level, the influence of capital adequacy on financial distress seems to be relatively minor.

In the case of *Operating Activities*, *Asset Turnover* (AsTo) exhibits a significant impact on the likelihood of financial distress, whereas *Revenue Growth* (RvG) shows limited influence. As a reflection of a FinTech firm's efficiency in generating revenues from asset investments, *Asset Turnover* mitigates the company's risk during economic downturns. While the coefficient linked to *Revenue Growth* lacks statistical significance, Vazquez and Federico (2015) argued that a more aggressive expansion before a crisis could increase the likelihood of failure, suggesting that rapid growth may not always be a good thing.

On the *Profitability* side, *Return on Assets* (RoA) seems to be the variable with the most substantial impact of this regression analysis. *Return on Assets* reflects the company's capacity to generate value, as solid earnings enable a FinTech firm to boost capital by increasing accumulated retained earnings that can create cushion to absorb shocks when a crisis happens. Therefore, a higher *Return on Assets* is expected to decrease the likelihood of distress. The results support this view as both 2019 and 2018 data provide evidence that *Return on Assets* is significantly negatively related to the likelihood of distress during the 2020-2021 COVID crisis. *Gross*

Margin (GM) reflecting a FinTech firm's competitive position also exhibits a statistically significant negative impact in all regressions.

Once the coefficients are estimated, it is necessary to consider the non-linear relationship. This analysis uses marginal effects to interpret the indirect relationships between independent and dependent variables. These impacts of incremental changes in explanatory variables are analyzed by setting each of them to their mean values. Table 5.2 presents the regression results for marginal effects and McFadden's Pseudo-R-squared calculated from the sample dataset of 2018 and 2019.

Table 5.2: Marginal Effects of 2018 and 2019

Marginal Effect	Logit 2019	Probit 2019	Logit 2018	Probit 2018
Debt Ratio	0.049*	0.056*	0.038	0.039
Current Ratio	-0.105	-0.107	-0.041	-0.043
Asset Turnover	-0.046***	-0.050***	-0.042***	-0.045***
Revenue Growth	-0.001	-0.001	-0.002	-0.002
Return on Assets	-0.048**	-0.057**	-0.124***	-0.143**
Gross Margin	-0.050***	-0.062***	-0.024	-0.033*
Observations	973	973	979	979
Distress	83	83	85	85
Normal	890	890	894	894
Pseudo R^2	0.080	0.085	0.075	0.077
AIC	536.219	533.335	548.399	547.104

Note: The dependent variable is Financial Distress (FD). Marginal Effect is shown as percentage value. The symbols ***, **, and * represent statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

The dependent variable in these models takes a value of one if a FinTech firm experienced financial distress during the 2020-2021 period, and zero otherwise. The first two columns present the marginal effect results based on data from 2019, one year before the COVID-19 pandemic happened, while the last two columns show the marginal effect results obtained from 2018 data, two years before the crisis.

The Pseudo-R-squared results show that when moving back in time from 2019 to 2018 while using the dependent variables collected from the 2020-2021 crisis period, the explanatory power of the logit and probit regression fall from 0.080 to 0.075 and from 0.085 to 0.077, respectively. Nevertheless, the marginal effects analysis reveals that most independent variables demonstrating significance in the models based on 2019 data also exhibit significance in the model from 2018 data. This persistence of significance across the two years preceding the observed dependent outcome of financial distress during the COVID crisis suggests the stability of the relationships between these variables and the likelihood of distress. The findings imply that *Asset Turnover* (AsTo), *Return on Assets* (RoA) and *Gross Margin* (GM) exhibit a sustained impact over time, reinforcing their relevance in predicting financial distress in FinTech firms even before the crisis.

On the other hand, the findings also reveal that some variables remain insignificant throughout the study period. *Current Ratio* (CR), reflecting short-term liquidity, has the expected sign but is not significant either in the 2018 or 2019 analyses. *Revenue Growth* (RvG), representing the change of firm revenue that is the main source of economic benefit of a firm, also exhibits the anticipated negative marginal effect on the likelihood of distress, indicating that growing faster could not help prevent a FinTech firm from getting into trouble during a crisis.

The marginal effect results clearly show that *Profitability* of FinTech firms represented by *Return on Asset* (RoA) and *Gross Margin* (GM) has the largest economic impacts. However, *Capital Adequacy* directly reflecting the level of indebtedness is less influential than expected.

Overall, the results suggest that variables commonly included in the Basel Accord, designed to enhance stability in traditional banks, may not be as relevant for explaining the likelihood of financial distress in digital financial platforms. The findings highlight that variables categorized under *Profitability* show a significantly stronger influence compared to those under *Capital Adequacy* in the CFS framework. This outcome underscores a critical insight for FinTech firms: prioritizing higher solvency over profit returns might not be advisable.

5.2 Non-financial variables

Theoretically, all 4 non-financial variables considered in this analysis should have negative impacts on the likelihood of FinTech firms being in financial distress, as digital finance platforms that are bigger, older, listed in a stock exchange, and operating in a developed market should be less likely to experience distress during a crisis. Table 5.3 presents the results for logit regression of each non-financial variable and previously analyzed CAMELS ratio variables based on data from 2019:

Table 5.3: Regression results with non-financial variables

Variable	(1)	(2)	(3)	(4)	(5)
Debt Ratio	0.002	0.009*	0.014***	0.008	0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Current Ratio	-0.018	-0.020	-0.020	-0.021	-0.024
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Asset Turnover	-0.005**	-0.008***	-0.006***	-0.009***	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Revenue Growth	-0.0004	-0.0003	-0.0001	-0.0002	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Return on Assets	-0.015***	-0.009**	-0.010***	-0.009**	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Gross Margin	-0.008**	-0.009***	-0.004	-0.010***	-0.005
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Size	0.233***				0.201***
	(0.055)				(0.057)
Age		-0.225			-0.450
		(0.322)			(0.343)
Public			1.429***		1.457***
			(0.289)		(0.301)
Location				0.337	0.769***
				(0.260)	(0.271)
Constant	-2.702***	-1.459***	-3.235***	-1.641***	-3.766***
	(0.494)	(0.489)	(0.542)	(0.408)	(0.640)
Observations	973	973	973	973	973
Log Likelihood	-251.823	-260.888	-247.136	-260.263	-263.612
AIC	519.646	537.776	510.272	536.525	495.223

Note: The dependent variable is Financial Distress (FD). The symbols ***, **, and * represent statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

The dependent variable in these models takes a value of one if a FinTech firm experienced financial distress during the 2020-2021 period and zero otherwise. The results of the explanatory data are calculated based on data from the 2019 annual reports. The non-financial variable *Size* is represented by the logarithm of the firm's assets in 2019. The other non-financial variables are dummy variables, meaning that *Age* takes a value of one if a firm is older than ten years, *Public* takes a value of one if a firm is publicly listed, and *Location* takes a value of one if a firm is located in a developed country, such as in Europe or North America.

The first to fourth columns present the effects of CAMELS ratio variables along with the impact of the non-financial variables *Size*, *Age*, *Public*, and *Location*, respectively. The last column reports the effects of CAMELS ratio variables and all non-financial variables together.

5.2.1 With the company Size effect

This paper uses the logarithm of the total assets value 2019, one year prior to the COVID-19 pandemic, to answer the question whether a larger FinTech company benefits from higher assets during a crisis. The *Size* value from the year preceding the dependent variable data is applied to mitigate concerns related to endogeneity, as the lagged company capital and financial performance can be determined interdependently.

The first column of Table 5.3 shows that *Size* exhibits significant and a positive correlation with the likelihood of distress. This finding contradicts the "too big to fail" hypothesis, a widely recognized concept suggesting that larger banks generally have higher survival odds than smaller banks during a crisis as larger institutions may benefit from political intervention or greater diversification, thereby enhancing their resilience in challenging economic conditions.

Larger FinTech firms may be more likely to experience financial distress during crises as they provide more digital credits to lower quality online consumers to gain market shares from traditional commercial banks, thus holding more toxic assets during an economic downturn, when those online customers are not able to pay back the loan. This finding is consistent with earlier results of Kočenda and Iwasaki (2020), which suggested that the economic impacts of the *Size* factor may vary between bank survival in Russia and the EU, influenced by differences in asset quality.

The result suggests that bigger FinTech firms holding a larger share of lower-quality assets may experience decreased profitability and operating performance during a crisis period, resulting in an increased likelihood of financial distress.

5.2.2 With the company Age effect

The result of the second column shows that the *Age* dummy variable plays no role in FinTech firms being in distress. The older financial firms are expected to be more stable with a sound standing, thus decreasing the distress likelihood. However, this paper finds that although the *Age* coefficient has the expected effect on financial distress, it is statistically insignificant.

As FinTech is a relatively new concept, many firms in this sector are engaged in creating novel business models. The rapidly evolving nature of the industry is characterized by digital finance platforms continually incorporating additional features into internet banking or developing new applications on mobile phones to attract online customers. Consequently, a longer operating history of FinTech firms does not necessarily guarantee a proven operational model for success in this dynamic and innovative industry.

5.2.3 With the Public listed effect

The statistically significant positive coefficient associated with the dummy variable *Public* indicates that FinTech firms listed on a stock exchange exhibit a higher likelihood of experiencing financial distress. This finding suggests that the status of being listed on a stock exchange may be associated with increased vulnerability for FinTech firms in times of economic challenges. This result is inconsistent with the view that listed commercial banks are likely to exhibit more resilience, since the stock exchange disclosure requirements bring more market discipline and better management, thus less likely to face financial difficulties during an economic downturn.

One reason to explain this result for listed FinTech firms may lie in their new business model and the nature of their customer base. Given that the customers of digital finance platforms are primarily internet users, who tend to be more responsive and sensitive to negative information during a financial crisis, the impact on FinTech firms can be significant. Unlike private firms that may not be subject to the same level of regulatory scrutiny, listed FinTech firms are obligated to timely announce any bad news, such as poor operating profit, typically within a quarter. This regulatory transparency can trigger a rapid reaction from digital customers, potentially leading to an online bank run and increasing the likelihood of financial distress events.

5.2.4 With the Location effect

The *Location* dummy variable, reflecting whether the FinTech firm operates in a developed country, acts as a macroeconomic factor in the regression analysis. The result shows that the coefficient of *Location* has a positive sign but is statistically insignificant, suggesting that higher legal standards and a more stable macroeconomic environment in developed countries are not significantly associated with a lower likelihood of individual FinTech firm being in distress.

This result contradicts the perspective that financial firms in better governed markets have a lower likelihood of distress. On the other hand, this analysis supports the view of Lin and Yang (2016) that firm-level fundamentals, such as financial ratios, play a more important role than macroeconomic factors or the broader economic environment. Specifically, CAMELS-type variables such as *Asset Turnover* (AsTo), *Return on Assets* (RoA), and *Gross Margin* (GM) are all found to be statistically significant relating to the likelihood of distress, with the expected negative signs.

5.2.5 All factors included

The last column of Table 5.3 shows the results of combining all non-financial variables and CAMELS-type explanatory variables. The Akaike Information Criterion (AIC) value of 495, the lowest of all models, indicates that including these additional firm characteristic variables enhances the explanatory capability of the logit regressions.

The coefficient results also suggest that *Return on Assets* (RoA), representing *Profitability* has consistently significant negative influences on financial distress in all regressions, even when considering all non-financial variables. *Size*, *Public*, and *Location* variables also keep their statistical significance even when all non-financial variables are added to a model.

5.3 Out-of-sample forecasting

The study period of this paper covers two global crises sparked by external factors: the COVID-19 pandemic in 2020 and the onset of the Ukraine war in 2022. The financial distress data from the COVID-19 period is utilized for training data, whereas the data from the Ukraine war period is reserved for out-of-sample testing.

In the previous section, logit regression is used to identify the factors that influence the financial distress of FinTech firms during the pandemic period from 2020 to 2021. The coefficients obtained from the model based on 2019 annual report data are subsequently applied to predict the financial distress of FinTech firms for the 2022-2023 period based on the 2021 data. This process serves as an out-of-sample accuracy check, measuring the model's effectiveness in making accurate predictions on data that it has not been directly trained on. By applying the coefficients obtained from the 2019 data to the 2021 dataset, the logit model's performance can be assessed in terms of its ability to generalize to new observations, thus providing valuable insights into its reliability and robustness.

5.3.1 Financial distress prediction

In the initial step, this paper uses the logit model results obtained from the 2019 dataset to predict outcomes for both the training dataset of 2019 and the testing dataset of 2021. The probability distribution outcomes are visually represented in Figure 5.1.

```
[1] "Train DataSet _ 2019"

  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.0000  0.0446  0.0739  0.0853  0.1096  0.8765

[1] "Test DataSet _ 2021"

  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.0000  0.0513  0.0790  0.0933  0.1187  0.8213
```

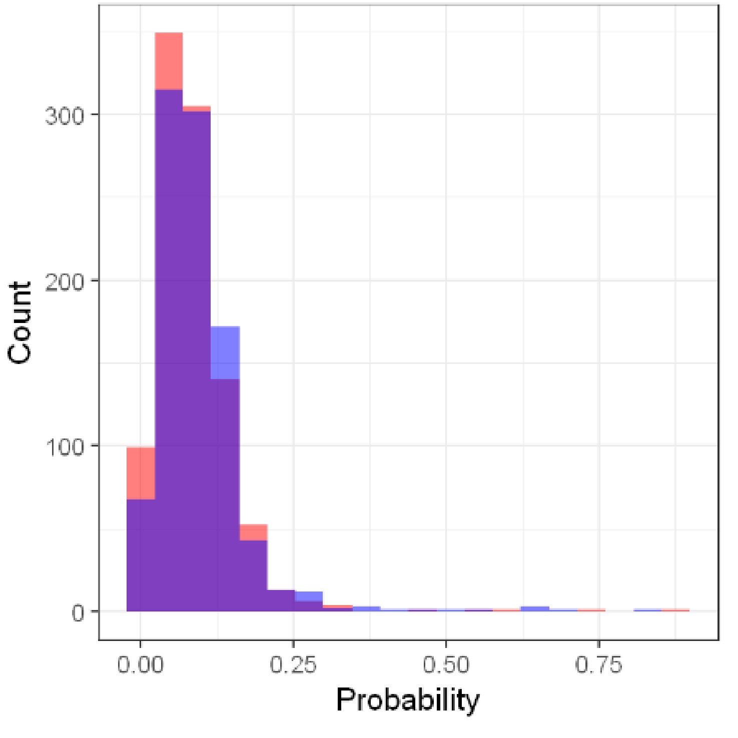

Figure 5.1: Distribution of predicted financial distress probability

The red bar is distribution of Financial Distress (FD) prediction from the training data (2019), while the blue bar is distribution of FD prediction from the testing data (2021).

The distribution results illustrate a similar distribution of predicted probabilities on both the training and testing datasets. The red bars represent the distribution of financial distress predictions from the training data, whereas the blue bars show the distribution of distress predictions from the testing data.

5.3.2 Prediction evaluation

This section uses the method of the ROC curves to evaluate the performance of the binary logit model. As explained in the methodology section, if the predicted probability for a sample exceeds a decision threshold, the sample is classified as positive. Subsequently, the true positive rate and false positive rate can be calculated based on this threshold.

The True Positive Rate (TPR, hit rate) is determined by dividing the number of true positives by the total number of positive instances. Conversely, the False Positive Rate (FPR, false alarm) is obtained by dividing the number of false positives by the total number of negative instances. The ROC curve graphically shows the relationship between these two rates.

Once the ROC curve is constructed, this paper can calculate the Area Under the Curve (AUC), the metric evaluating the model's capacity to differentiate between positive and negative instances. Higher AUC values indicate better performance, reflecting a better separation between positives and negatives. Figure 5.2 displays the prediction performance on both the training and testing datasets using the ROC curves and their corresponding AUC values.

```
[1] "Train - Area under the curve (AUC): 0.726"
[1] "Test - Area under the curve (AUC): 0.672"
```

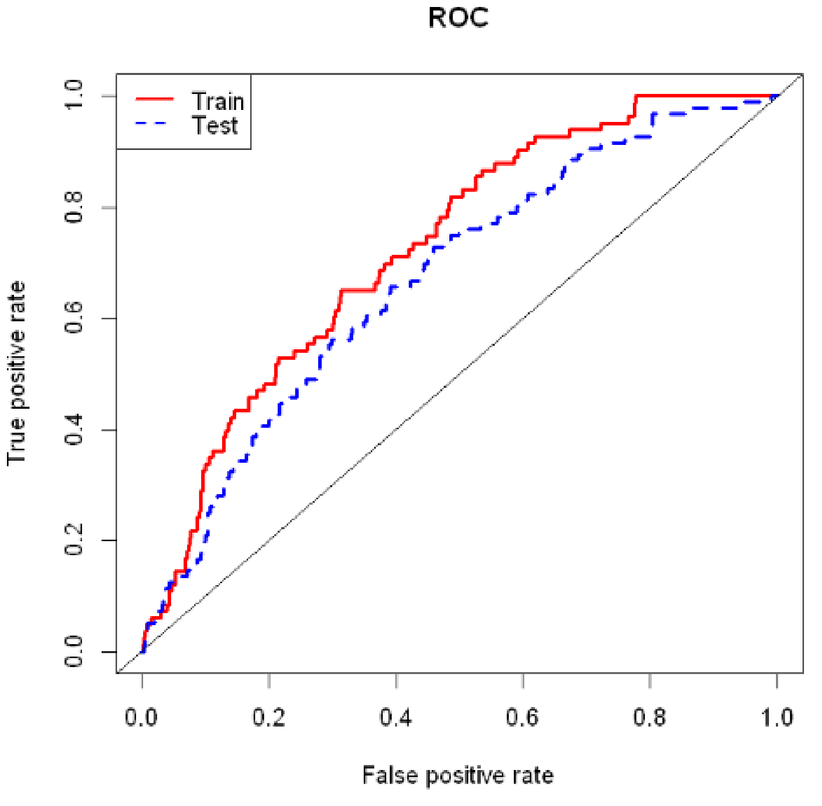

Figure 5.2: ROC curve of training and testing data prediction results

The red solid curve is the ROC prediction for training data (2019), while the blue dash curve is the ROC prediction for testing data (2021).

The True Positive Rate (TPR) and False Positive Rate (FPR) are computed and illustrated in the ROC graph at each cutoff point. The red solid curve represents the ROC prediction for the training data, while the blue dashed curve represents the ROC prediction for the testing data. Additionally, a 45-degree line is plotted on the graph, representing random guessing. The further the ROC curve is from this diagonal line, the better the model's performance.

As expected, the prediction performance of testing data is worse than that of training one. The graph also shows that gains in TPR come at the expense of a rise in FPR. However, the objective of this paper is not to identify a superior failure prediction model but rather to compare the impact of different types of CAMELS variables. Therefore, the analysis focuses solely on financial independent variables, which may result in a relatively lower AUC.

6 Robustness Check

This paper considers three robustness check methods. Firstly, this section discusses the rare event issue of the dataset. Secondly, the ordered response model is applied as an alternative approach to compare the regression results. Finally, variable selection bias is handled using the Bayesian Model Average (BMA) method.

6.1 Dataset: Rare event issue

To address the issue of rare events, this paper employs various techniques to obtain a balanced dataset, including over-sampling, under-sampling, and bootstrapping of the original 2019 dataset. The results of logit regression applied to each rebalanced dataset generated from these methods are presented in Table 6.1.

Table 6.1: Logit regression results of ROSE rebalancing dataset

Variable	Over-sampling	Under-sampling	Combination	Bootstrapped
Debt Ratio	0.010***	0.015*	0.007**	0.009***
	(0.002)	(0.008)	(0.003)	(0.003)
Current Ratio	-0.024**	-0.036	-0.043**	-0.001
	(0.010)	(0.025)	(0.020)	(0.001)
Asset Turnover	-0.010***	-0.013***	-0.010***	-0.005***
	(0.001)	(0.004)	(0.001)	(0.001)
Revenue Growth	-0.0001	-0.0003	-0.0002	-0.0001
	(0.0002)	(0.001)	(0.001)	(0.0001)
Return on Assets	-0.015***	-0.022***	-0.026***	-0.014***
	(0.003)	(0.010)	(0.005)	(0.003)
Gross Margin	-0.016***	-0.022***	-0.016***	-0.012***
	(0.003)	(0.007)	(0.003)	(0.002)
Constant	1.101***	1.549**	1.377***	0.501**
	(0.191)	(0.683)	(0.292)	(0.200)
Observations	1170	160	973	973
Log Likelihood	-1061.722	-90.814	-567.565	-599.384
AIC	2137.444	195.628	1149.130	1212.767

Note: The dependent variable is Financial Distress (FD). The symbols ***, **, and * represent statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

The first column in Table 6.1 displays results based on over-sampling data, the second column presents results based on under-sampling data, the third column shows results from data created by using the combination of over-sampling and under-sampling techniques, and the last column presents results based on bootstrapped data.

The regression results indicate that all variables exhibit the expected sign, with *Debt Ratio* (DR), *Assets Turnover* (AsTo), *Return on Assets* (RoA), and *Gross Margin* (GM) being significant across all datasets. *Current Ratio* (CR) shows significance in some rebalanced datasets, whereas *Revenue Growth* (RvG) does not demonstrate significance in any regression. These findings support the baseline analysis outcomes, suggesting that the effects of *Profitability*-related variables are significantly stronger than those of *Capital Adequacy*-related variables.

Overall, the regression results calculated from the rebalanced dataset demonstrate that the original logit regression results are robust. This robustness can be partially attributed to the original sample size, which consists of approximately 1000 observations with nearly 100 distressed FinTech firms, suggesting that the occurrence of events is not so rare to significantly bias the evaluation outcomes.

6.2 Modeling: Ordered response models

An ordered logit model is applied to conduct a robustness check for the baseline logit regression results of the COVID-19 study period. The dependent variable takes on three different values (0, 1, or 2) depending on whether a FinTech firm is operating normally, distressed, or failing. The approach assumes that the financial status of a FinTech firm can be ordered from *Normal* to *Distress*, then *Fail*. The regression results of the ordered logit model are reported in Table 6.2.

Table 6.2: Result of ordered logit regression

Variable	Estimate	Std. Error
Debt Ratio	0.009*	(0.005)
Current Ratio	-0.021	(0.025)
Asset Turnover	-0.009***	(0.022)
Revenue Growth	-0.0002	(0.001)
Return on Assets	-0.011***	(0.004)
Gross Margin	-0.010***	(0.003)
Observations	973 (Normal 890, Distress 71, Fail 12)	
Threshold 0|1	1.600	(0.404)
Threshold 1|2	3.683	(0.481)

Note: The dependent variable is Financial Distress (FD). The symbols ***, **, and * represent statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

The reported results represent the outcome of the ordered logit regression for *Normal*, *Distress*, and *Fail* FinTech firms. The dependent variable takes values of 0, 1, or 2 according to whether a FinTech firm is operating normally, distressed, or failing. The sample comprises 973 observations, of which 12 are failing, 71 are distressed, and 890 are normally operating FinTech firms.

The ordered logit regression confirms the robustness of the results since all coefficients have the same signs as those of the baseline logit regression. *Asset Turnover* (AsTo), *Return on Assets* (RoA), and *Gross Margin* (GM) are all statistically significant. *Debt Ratio* (DR) is only significant at the 0.1 level, while *Current Ratio* (CR) and *Revenue Growth* (RvG) show no significance. This outcome confirms that *Operating Activities* and *Profitability* are more important than *Capital Adequacy*. In addition, Table 6.3 presents the results of the original binary logit and probit regressions together with the results of the ordered logit and probit models.

Table 6.3: Results for ordered response regression

Variable	Logit binary	Probit binary	Logit ordered	Probit ordered
Debt Ratio	0.009*	0.005*	0.009*	0.005**
	(0.005)	(0.003)	(0.005)	(0.003)
Current Ratio	-0.019	-0.009	-0.021	-0.011
	(0.024)	(0.011)	(0.025)	(0.012)
Asset Turnover	-0.008***	-0.004***	-0.009***	-0.004***
	(0.002)	(0.001)	(0.002)	(0.001)
Revenue Growth	-0.0002	-0.0001	-0.0002	-0.0001
	(0.001)	(0.0004)	(0.001)	(0.0005)
Return on Assets	-0.009**	-0.005**	-0.011***	-0.006***
	(0.004)	(0.002)	(0.004)	(0.002)
Gross Margin	-0.009***	-0.005***	-0.010***	-0.006***
	(0.003)	(0.002)	(0.003)	(0.002)
Constant	-1.644***	-0.959***		
	(0.406)	(0.206)		
Observations	973	973	979	979
Log Likelihood	-261.110	-259.668	-293.264	-289.326
AIC	536.219	533.335		

Note: The dependent variable is Financial Distress (FD). The symbols ***, **, and * represent statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

The first two columns of Table 6.3 display the results of logit and probit binary choice regressions for CAMELS ratios of 2019, which serve as the baseline models. The last two columns present the results of the ordered logit and probit regressions on the same training data.

Overall, the results reported appear robust to changes in the methodology of the model estimation, from binary choice to ordered response models, along with the application of a new definition for financial distress levels applied to the original dataset.

6.3 Variables: BMA analysis

This section presents the results of the robustness check obtained from analyzing the baseline dataset from 2019 using the Bayesian Model Averaging (BMA) approach for variable selections.

As the posterior probability estimates in the BMA analysis depend on the data obtained from Bayesian inference, the BMA method should be applied to the baseline dataset without rebalancing to keep the original characteristics. The main objective of this section is to use this approach to identify the most influential explanatory variables for each group of the CFS framework. Furthermore, this section examines the consistency of the results from the robustness check by evaluating a set of variables selected manually or through the MBA method.

This paper uses a uniform distribution of model priors for the distribution of regression coefficients to ensure that all models are given the same prior probability without any preference. Given the annual report data availability, only 9 CAMELS ratios are collected for this study, allowing the BMA analysis to use the complete enumeration of the 512 models. The results of the BMA analysis are presented in Table 6.4.

Table 6.4: Determinants of financial distress from BMA analysis

Variable	PIP	Mean	SD
Profit Margin	0.831	-0.0003	0.0001
Asset Turnover	0.397	-0.0000	0.0001
Return on Assets	0.296	-0.0004	0.0010
Gross Margin	0.293	-0.0002	0.0003
Return on Equity	0.151	-0.0000	0.0000
Debt Ratio	0.149	0.0001	0.0003
Leverage Ratio	0.040	-0.0000	0.0001
Revenue Growth	0.033	-0.0000	0.0000
Current Ratio	0.033	0.0000	0.0000

Note: The dependent variable is Financial Distress (FD).

The first column in Table 6.4 displays the posterior inclusion probabilities (PIP), indicating the likelihood of each variable being part of the final model. The PIP values are arranged in descending order. The second column presents the posterior means, while the third column shows the posterior standard errors. The primary statistic result within the findings is the PIP, which serves as an indicator of the significance attributed to each variable's inclusion. (Havranek et al., 2017).

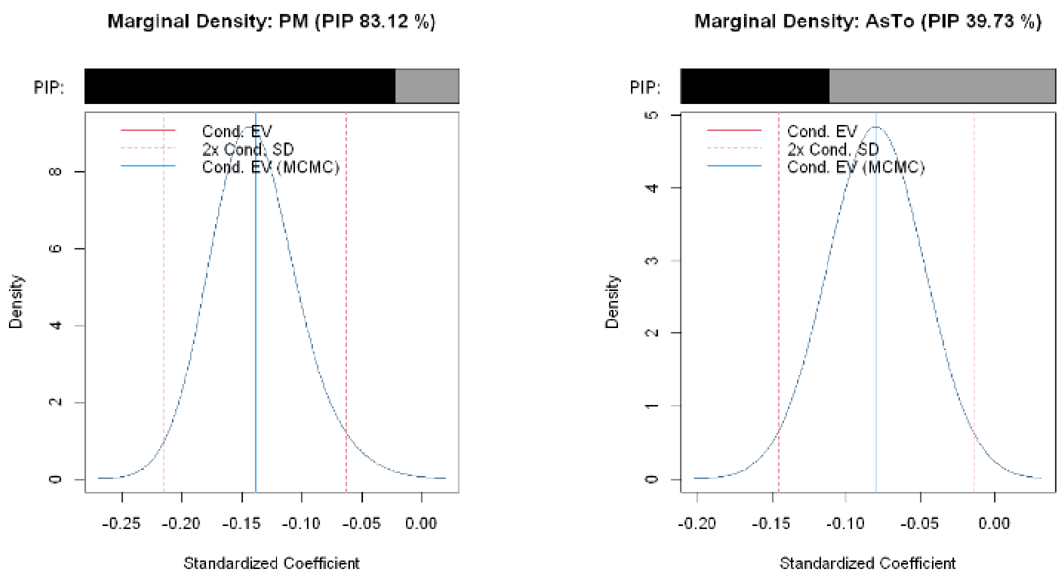

Figure 6.1: Posterior densities of variables with the highest PIPs

The marginal posterior distribution of the two variables with the highest posterior inclusion probability (Profit Margin and Assets Turnovers). Bar charts located at the top of the graphs show the posterior inclusion probability for the corresponding independent variable.

Figure 6.1 depicts the marginal posterior distribution of the two variables with the highest PIP. The bar charts at the top of the graphs show the posterior inclusion probability for the corresponding independent variable. The marginal densities portrayed in the charts embody the posterior distribution of the regression coefficient if the corresponding variables are included in the model. The two coefficients depicted in the figure indicate the impacts on financial distress of two key CAMELS ratios: *Profit Margin* (PM) and *Assets Turnover* (AsTo).

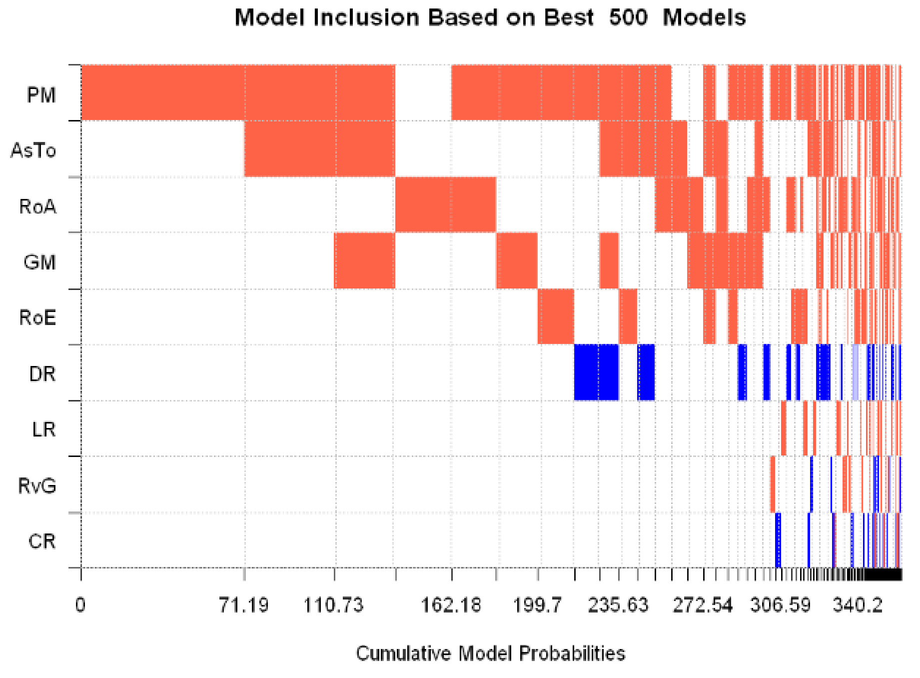

Figure 6.2: Results of BMA model inclusion

The response variable is the estimated financial distress parameter. The columns represent individual models. The horizontal axis represents cumulative posterior model probabilities. Only the top 500 models with the highest posterior probabilities are displayed. The variables are arranged in descending order according to posterior inclusion probability. Blue indicates that the variable is included with a positive estimated sign; Red indicates inclusion with a negative estimated sign; No color indicates exclusion from the model.

Figure 6.2 presents the results of the BMA analysis. Each column in the figure represents an individual model, with the horizontal axis representing cumulative posterior model probabilities. The variables are arranged in descending order according to their posterior inclusion probability. Blue in the graph indicates that the variable is included in the model with a positive estimated sign, while red demonstrates inclusion with a negative estimated sign. If a variable is not colored, it is excluded from the model. Additionally, the regression signs remain stable for all variables with a posterior inclusion probability greater than 0.05.

Following the BMA analysis, this paper conducts a correlation check to pinpoint the suitable variables for selection based on the highest PIP. Given that the objective of this paper is to compare the importance of variables from the CFS framework, it is necessary to select at least one variable for each of the three categories. Consequently, four of the most crucial variables are chosen from the BMA analysis, including the *Debt Ratio* (DR) for *Capital Adequacy*, *Asset Turnover* (AsTo) for *Operating Activities*, and *Return on Assets* (RoA) and *Gross Margin* (GM) for *Profitability*.

With the BMA-selected variables, this paper once again applies both logit and probit models to the baseline training dataset. The results of these regressions are presented in Table 6.5.

Table 6.5: Results for binary choice models with BMA selected variables

Variable	Logit baseline	Probit baseline	Logit BMA	Probit BMA
Debt Ratio	0.009*	0.005*	0.010**	0.006***
	(0.005)	(0.003)	(0.005)	(0.002)
Current Ratio	-0.019	-0.009		
	(0.024)	(0.011)		
Asset Turnover	-0.008***	-0.004***	-0.008***	-0.004***
	(0.002)	(0.001)	(0.002)	(0.001)
Revenue Growth	-0.0002	-0.0001		
	(0.001)	(0.0004)		
Return on Assets	-0.009**	-0.005**	-0.009**	-0.005**
	(0.004)	(0.002)	(0.004)	(0.002)
Gross Margin	-0.009***	-0.005***	-0.009***	-0.005***
	(0.003)	(0.002)	(0.003)	(0.002)
Constant	-1.644***	-0.959**	-1.810***	-1.041**
	(0.406)	(0.206)	(0.369)	(0.189)
Observations	973	973	973	973
Log Likelihood	-261.110	-259.668	-262.024	-260.567
AIC	536.219	533.335	534.047	531.134

Note: The dependent variable is Financial Distress (FD). The symbols ***, **, and * represent statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

The response variable in these models takes a value of one if a FinTech firm experienced financial distress during the 2020-2021 period and zero otherwise. The results of the explanatory data are calculated based on data from the 2019 annual reports. The first two columns in Table 6.5 show the results derived from the regression using the CAMELS variables selected manually, while the last two columns display the results obtained using the BMA-selected variables. The regression results validate the earlier findings from baseline logit regression, as all coefficients of the CAMELS variables show the expected signs, with *Operating Activities* and *Profitability* variables demonstrating greater significance compared to *Capital Adequacy* variables. Specifically, *Debt Ratio* (DR) is only significant at the 0.05 level, while both *Asset Turnover* (AsTo) and *Gross Margin* (GM) are significant at the 0.01 level.

The results from Table 6.5 indicate that BMA regressions exhibit superior performance by achieving lower Akaike information criterion (AIC) values with fewer variables. With the BMA method reducing the number of variables from 6 to 4 by excluding *Credit Ratio* (CR) and *Revenue Growth* (RvG), both the logit and probit regression models show a decrease in AIC, dropping from 536 to 534 and from 533 to 531, respectively. Given that lower AIC values suggest a better model fit, the elimination of these two variables by the BMA analysis is justified.

This paper uses the BMA-selected variables and the training dataset from the COVID-19 period to construct a BMA-based logit model shown in the third column of Table 6.5. This model is then applied to the out-of-sample Ukraine war period testing dataset to forecast the likelihood of FinTech firms experiencing distress. Figure 6.3 illustrates the results comparing the prediction performance of the logit model using manually selected variables from section 5.3.2 with that of the model using BMA-selected variables.

```
[1] "BMA - Area under the curve (AUC): 0.68"
[1] "Baseline - Area under the curve (AUC): 0.672"
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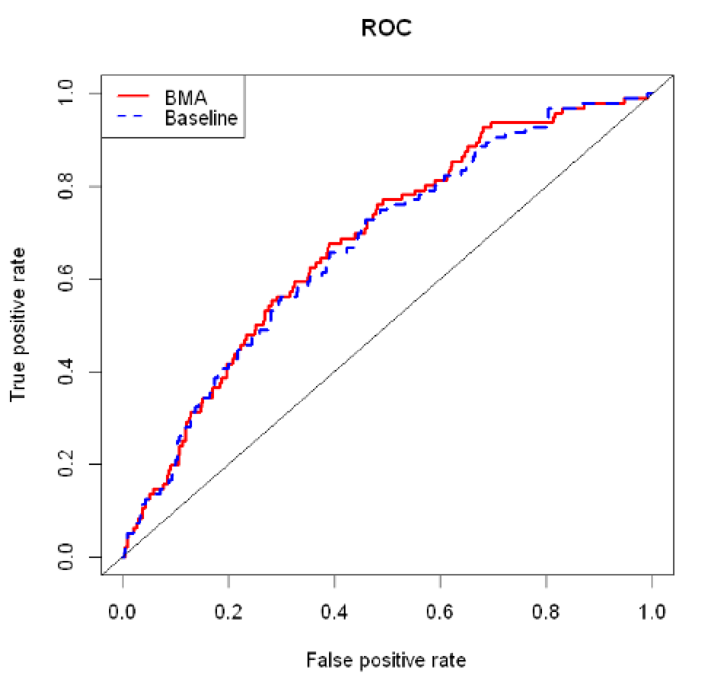

Figure 6.3: BMA predictive performance

The red solid curve illustrates the ROC prediction from BMA-selected variables, whereas the blue dashed curve represents the ROC prediction from manually selected variables. Both predictions are based on the logit model.

Figure 6.3 displays the ROC predictions, with the red solid curve representing the BMA-selected variables and the blue dashed curve representing the variables selected manually based on the correlation matrix. Both predictions employ the logit model. The chart demonstrates that the two lines are almost identical. Additionally, the AUC results of 0.680 versus 0.672 indicate no significant difference between the models selected manually and those selected via the BMA approach. As this paper primarily concentrates on analyzing financial CAMELS variables, non-financial variables are excluded from the BMA analysis, potentially leading to relatively low AUCs. It is noteworthy that the BMA model utilizes fewer variables. Kočenda and Vojtek (2011) noted that when the ROC shapes of two models are similar, the one with fewer variables is preferred, due to the principle of parsimony. Therefore, the BMA method is favored in this analysis.

Overall, the reported results appear to be robust to changes in the variable selection approach for the logit model, specifically manual selection and the BMA method.

7 Conclusion

Motivated by the rapid growth of the FinTech sector, this paper investigates the impacts of capital adequacy, operating activities, and profitability factors on the likelihood of FinTech firms experiencing financial distress during the crisis period. On top of the traditional CAMELS ratios used for evaluating traditional commercial banks, this paper takes a new approach based on the CFS framework, which considers the financing, operating, and investing aspects of FinTech firms. The analysis uses a cross-country dataset during the COVID-19 crisis, with logistics regression as the baseline model.

The main findings of this paper can be summarized as follows. The analysis shows that profitability plays a more significant role in ensuring the soundness of FinTech firms compared to capital adequacy. FinTech firms with higher profitability before a crisis are less likely to experience financial distress. In terms of solvency and liquidity, only the debt ratio shows a limited impact, with significance found only at the 10% level, while the current ratio lacks statistical significance. This paper conducts several robustness checks through rare event data management, ordered modeling approaches, and the BMA variable selections, with the results remaining consistent relative to the baseline estimates.

These results challenge the commonly held belief that capital inadequacy is the primary source of financial instability in financial institutions. Instead, this analysis suggests that within the FinTech sector, prioritizing higher solvency at the expense of profit returns may not be an efficient way to mitigate financial risk. Although traditional views emphasize the importance of strong capital positions for financial stability, this paper implies that profitability factors may play a more substantial role in ensuring the resilience and soundness of FinTech firms.

The conclusions of this paper offer evidence for the ongoing debate regarding the effectiveness of capital cushions in enhancing bank stability, particularly when considering the potential conflict with profitability. Policymakers should avoid applying the same regulatory frameworks to digital finance platforms as those designed for traditional commercial banks directly. Additionally, this analysis implies that regulating digital banks solely by following Basel III Accord rules, which primarily address structural liquidity and capital, may not be appropriate. Instead, this paper underscores the importance of a balanced approach where FinTech firms carefully weigh the trade-offs between capital adequacy and operational profitability.

Nonetheless, this paper has some limitations. Even though it examines the impact of various factors on FinTech firms, the time frame is relatively narrow due to a lack of data availability. Although the regression results appear robust, they provide only preliminary evidence. Further research should re-examine this relationship once data on FinTech firms' bankruptcies over a longer business cycle becomes available.

In the future, the research could focus on a comparison among traditional banks, Big Tech companies, and FinTech firms. Such an examination would offer valuable insights into the different impacts of financial factors within the CFS framework on the likelihood of experiencing financial distress. Furthermore, collecting data from Cash Flow Statements to calculate more financial ratios for regression analysis would be beneficial. Additionally, comparing results from alternative regression models, such as Z-score and hazard models, would provide a more comprehensive understanding of the financial factors under consideration.

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Appendix A: Data collection process

The screenshot displays the sample dataset obtained from the S&P Capital IQ database using a customized filter that identifies FinTech firms experiencing financial distress.

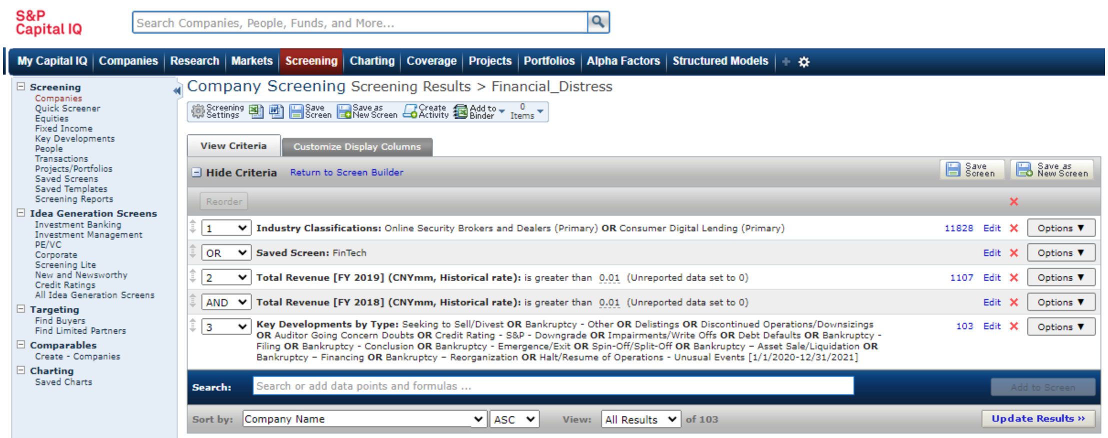

Figure A.1: Customized filter of defining financial distress

The screener tool provided by S&P database allows this paper to filter out the distressed FinTech firms during the sample period (2020-2021) by defining specific event indicators, including "Seeking to Sell", "Bankruptcy", "Discontinued Operations", "Auditor Going Concern Doubts", "Credit Rating Downgrade", and "Debt Defaults".

Then, the sample data was downloaded as an Excel file and imported into R code.

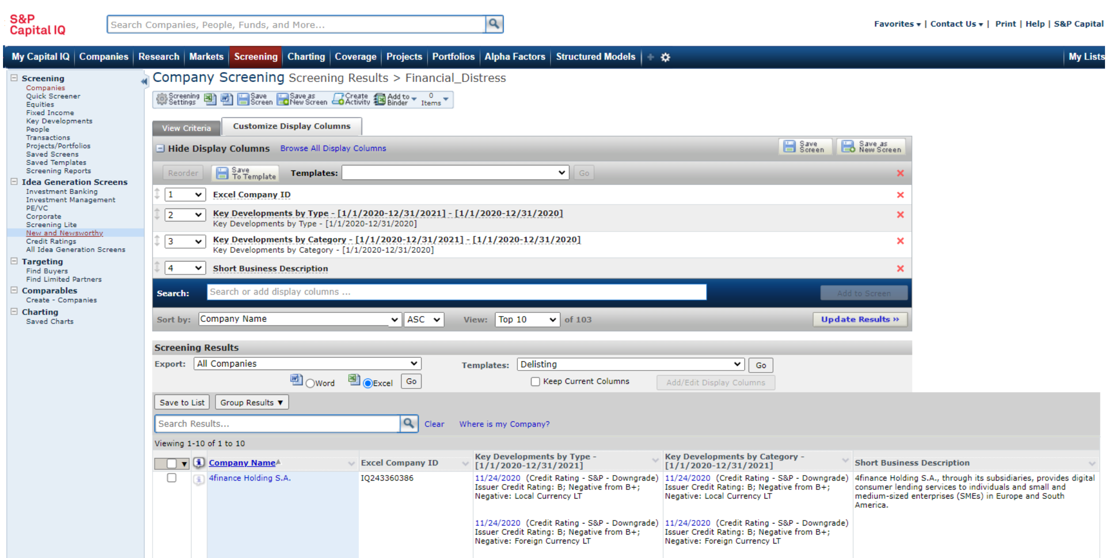

Figure A.2: Retrieve FinTech firms' data from distressed events

Appendix B: BMA analysis results

The following figures represent the outcomes from BMA analysis.

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
PM	0.83122194	-0.00027248041121	0.00014733747	0.0000000	9
AsTo	0.39730876	-0.00004759410899	0.00006626369	0.0000000	4
RoA	0.29582621	-0.00037581412905	0.00065180448	0.0000000	6
GM	0.29320895	-0.00017664127100	0.00031031630	0.0000000	8
RoE	0.15122981	-0.00000478227523	0.00001320818	0.0000000	7
DR	0.14910828	0.00010047891893	0.00027878987	1.0000000	1
LR	0.04010651	-0.00000763982080	0.00007538568	0.0000000	2
RvG	0.03339080	-0.00000002468938	0.00000137839	0.3917090	5
CR	0.03319477	0.00000071995715	0.00002230798	0.8245386	3

Mean no. regressors	Draws	Burnins	Time
"2.2246"	"512"	"0"	"0.05153418 secs"
No. models visited	Modelspace 2^K	% visited	% Topmodels
"512"	"512"	"100"	"98"
Corr PMP	No. Obs.	Model Prior	g-Prior
"NA"	"973"	"uniform / 4.5"	"UIP"
Shrinkage-Stats			
"Av=0.999"			

Time difference of 0.05153418 secs